Spot Wages over the Business Cycle?[*]

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August 26, 2009

Abstract

We consider a model with on-the-job search where current wages depend only on current aggregate labor market conditions and match-specific idiosyncratic productivities. We nevertheless show that the model replicates findings which have been interpreted as evidence against a spot wage model. Past aggregate labor market conditions such as the unemployment rate at the start of the job, the lowest unemployment rate since the start of a job, or the number of outside job offers received since the start of the job have explanatory power for current wages since these variables are correlated with procyclical match qualities. The business-cycle volatility of wages is higher for newly hired workers than for job stayers since workers can sample from a larger pool of job offers in a boom than in a recession. Using NLSY and PSID data, we find that the existing evidence against a spot wage model is rejected once we control for match-specific productivity as implied by our theory.

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1 Introduction

Understanding the behavior of wages over the business cycle is a classic yet still an open question in economics. One view is that in every period of time a worker's wage reflects only her contemporaneous idiosyncratic productivity and the contemporaneous aggregate influences. Although there is disagreement about what these aggregate factors are - for example, productivity shocks as in Kydland and Prescott (1982) and Long and Plosser (1983) or government spending shocks as in Aiyagari, Christiano, and Eichenbaum (1992) - these papers share the view that the wages are spot. The spot wage setting does not have to be Walrasian, it could be, e.g., bargaining as in the typical search model. What is important is that it is the current state of the economy, affected by either aggregate productivity or the amount of government spending, and the current idiosyncratic worker productivities that determine the outcomes in the labor market and, in particular, wages.

Although the spot wage model is a workhorse of modern quantitative macroeconomics, the wisdom of relying on this assumption has been questioned in a number of influential studies. These studies presented evidence that several (often complicated) functions of histories of aggregate labor market conditions serve as important determinants of wages even after the current aggregate and idiosyncratic conditions have been taken into account. These findings suggest that models that incorporate some form of real wage rigidity would deliver a better description of actual labor markets.

Multiple empirical findings in the literature were interpreted as providing support for the view that wages are rigid and inconsistent with the spot wage model. In a seminal contribution, using individual data, Beaudry and DiNardo (1991) find that wages depend on the lowest unemployment rate since the start of a job much stronger than on the current unemployment rate. This fact is consistent with the presence of insurance contracts through which firms insure workers against fluctuations in income over the business cycle but not with a spot wage model.[1] A large literature, started by another seminal contribution by Bils (1985), finds

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[1] The lowest unemployment rate during a job spell is an important determinant of wages if firms insure workers against fluctuations in income over the business cycle and firms can commit to the contract and workers cannot. Under such contracts firms do not adjust wages downward in recessions to insure workers but they have to adjust them upwards when labor markets are tight, i.e., when unemployment rates are low and workers can easily find other jobs.

that wages of newly hired workers are more procyclical than wages of workers who stay in their jobs. Relatedly, the slope of the tenure profile changes over the business cycle so that the cross-sectional returns to tenure are higher in a recession than in a boom. This appears inconsistent with a spot wage model. Instead, this finding suggests that workers hired in a recession are not shielded from the adverse business cycle conditions leading to large wage difference relative to higher tenured workers hired earlier. In a boom the opposite is true, and the wage differential between low and high tenure workers is much smaller. Furthermore, it has been found that recessions have a persistent impact on subsequent wages and that the business cycle conditions at the time of entering the labor market matter for future wages (e.g., Bowlus and Liu (2007) document this for high school graduates and Kahn (2007), Oreopoulos, von Wachter, and Heisz (2008) for college graduates). Those who enter the labor market in a recession have persistently lower wages than those who enter in a boom. All these findings point to a conclusion that a spot wage model is not a good description of actual wage dynamics over the business cycle and models that incorporate real wage rigidities might provide a better description.

In this paper we question this conclusion. We show that all these observations, although clearly not consistent with a Walrasian labor market, are consistent with a standard search model that does not feature any rigidity or built-in history dependence of wages and where current wages depend on current aggregate labor market conditions and on idiosyncratic productivities only. In our model, workers receive job-offers (with a higher probability in a boom than in a recession), which they accept whenever the new match is better than the current one. The number of offers a worker receives helps predict the quality of the match he is in. A higher number of offers increases expected wages since either more offers have been accepted or more offers have been declined which reveals that the match has to be of high quality. Using this model, we make a theoretical and an empirical contribution.

We show theoretically that our model leads to selection effects with respect to idiosyncratic match productivity that can explain all the facts mentioned above that have been interpreted as evidence for wage rigidities. We demonstrate that the number of offers received by the worker during each completed job spell measures this idiosyncratic productivity. Since the lowest unemployment rate during a job spell is negatively correlated with the number of offers

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received during a job spell, it does have explanatory power in our model as well, despite the fact that our model features spot wages only. The same result applies to the labor market conditions at the beginning of the job spell. A high unemployment rate is associated with a small number of job offers and thus with low wages. Finally, we show that the wages of new hires are more volatile than the wages of stayers, because workers can sample from a larger pool of job offers in a boom than in a recession, and workers with a lower quality of the current match benefit more from the expansion of the pool of offers in a boom.

For the empirical implementation of this idea we propose a method to measure the expected match quality, a variable which is not directly observable. Our theoretical result establishes that the expected number of offers during a job spell measures the expected match quality. However the expected number of offers is also not directly observable. The key insight is that the sum of labor market tightness (the ratio of the aggregate stock of vacancies to the unemployment rate) during the job spell measures the expected number of offers. Since labor market tightness is observable, this enables us to measure the expected match quality through an observable variable.

Having developed a way to measure the expected match quality in the data we are able to test our theory. We include the sum of labor market tightness during a job into wage regressions that have been viewed as providing evidence favoring the rigid wage interpretation of the data. We use data from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics. We find that our measure of match quality is indeed important in explaining current wages. In a direct test of "rigidity variables" and our search model, we find that wage rigidities are clearly rejected in favor of the spot wage model. Relatedly, we find that the aggregate conditions at the start of the job lose any significance once match quality is controlled for consistently with our theory. Moreover, we show that wages of job stayers and switchers exhibit similar volatility once we control for our selection effects using the regressors we derived and that there is no significant difference between the slopes of tenure profiles in a recession and in a boom.

We also apply our methodology to assess the empirical performance of models that feature a different type of wage rigidity. In many search models (e.g., Postel-Vinay and Robin (2002), Cahuc, Postel-Vinay, and Robin (2006)) it is assumed that firms and workers can commit to

future wages and firms can credibly counter offers from other firms. In such models workers who received more offers in their current job and stayed have received more counter offers which implies an increase in wages. Consequently, the expected number of offers received since the beginning of the job up to date t is an important predictor of wages at date t. We show that this is indeed the case empirically if one does not control for match qualities. However, the expected number of offers received since the beginning of the job until period t becomes insignificant once we account for, as implied by our theory, the expected number of offers received during the completed job spell. Whereas the number of offers received until period t just reflects past labor market conditions, measuring unobserved match quality requires to use all offers received during the job spell. This provides a sharp distinction between our regressor and those implied by models with contracts or commitment. In contrast to the predictions of contracting models, we find that future aggregate labor market conditions help predict wages at date t. This is consistent with the search model where future labor market conditions help reveal idiosyncratic match productivity.

Several additional well known criticisms of the spot wage model are specific to the real business cycle literature. The failures listed for example by Gomme and Greenwood (1995) and Boldrin and Horvath (1995) include that real wages are less volatile than total hours, that the labor share of total income is not constant, and that real wages are not strongly procyclical. We do not address these failures because they do not arise in a standard search model[2], very similar to the one we use in this paper.

The two different views of wage formation - spot wages or rigidities - have radically different implications for the macroeconomy. Whereas incorporating either wage rigidities or search frictions will improve the performance of the labor market in, say, a real business cycle model, many implications of the model (e.g., efficiency properties) will be very different. In addition, this modeling choice may lead to different answers to important policy questions, depending on one's view of wage formation. For example, what are the causes for the persistent effects of recessions? Are these effects inefficient or just reflect optimal responses to a changing environment? Should and can government policy overcome these effects? Taking into account these persistent effects, are the welfare costs of business cycles negligible as suggested by Lucas

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[2]In particular, if calibrated as in Hagedorn and Manovskii (2008).

(1987, 2003), or not as suggested by Krebs (2007)?

Relatedly, in the literature on the quantitative analysis of labor search models, the behavior of wages is a key input to assess the model's success (Pissarides (2008)). The amount of rigidity in wages distinguishes different calibration strategies with radically different implications. Current consensus in the literature is that aggregate wages are pro-cyclical and quite volatile. However, this relatively high aggregate wage elasticity can be achieved by (1) wages of all workers being roughly equally cyclical, or (2) wages of workers in continuing relationships being relatively rigid while wages of workers in new matches being highly volatile. Our findings support the interpretation of the data where wages in all matches respond roughly similarly to fluctuations in aggregate productivity once changes in match qualities are accounted for.[3]

Finally we would like to emphasize that the method that we develop to measure the expected match quality is not only a key step enabling the empirical analysis in this paper, but has a much wider applicability. For example, it is well known that the presence of substantial unobservable match-specific capital causes severe identification problems when estimating the returns to seniority (Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991)). A potential solution to this problem is to develop and estimate a dynamic model of on-the-job search, which however has to be parsimonious in many respects and thus cannot account for the typical complexity of wage regressions (Eckstein and Wolpin (1989)). Our method suggests a simpler strategy that is nevertheless completely consistent with a structural model. We expect that controlling for match quality through the sum of labor market tightness eliminates these identification problems and will deliver an unbiased estimate of the returns to tenure.

The paper is organized as follows. In Section 2 we derive the wage regression equation that must be satisfied in almost any model with on-the-job search and spot wages. In Section 3, we show theoretically that a spot wage model with on-the-job search gives rise to all the evidence that was interpreted as favoring rigid wages. The reason is that the "rigidity variables" imperfectly proxy for the idiosyncratic match quality which is not controlled for

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[3]This implies that the elasticity of wages of job stayers is a better empirical measure that can be used to identify the worker's bargaining power than the wage elasticity of new hires, unless the changes in match qualities are accounted for. Our finding of no significant differences (once we control for selection) between the cyclical behavior of wages of stayers and newly hired workers lends support to the key assumption in, e.g., Gertler and Trigari (2009).

in the regressions. The model also reproduces higher wage volatility of new hires unless the quality of their matches is accounted for. In Section 4 we describe our empirical methodology. In Section 5 we perform an empirical investigation using the PSID and NLSY data and find that the evidence that was interpreted to support rigidity in wages is rejected in favor of the spot wage model with on-the-job search. In Section 6 we parameterize and simulate our theoretical model. The main question we ask in this Section is what is the extent of frictions required to quantitatively account for all the evidence favoring rigid wages. We find that the amount of frictions required is small. In particular, less than 5% of the variance of log wages in the data must be attributable to search frictions for our model to match all the evidence on "wage rigidities". Section 7 concludes.

2 Theory

2.1 The environment

A continuum of workers of measure one participates in the labor market. At a moment in time, each worker can be either employed or unemployed. An employed worker faces an exogenous probability s of getting separated and becoming unemployed (we will allow for endogenous separations later). An unemployed worker faces a probability λ_θ of getting a job offer. By the word "offer" we mean a contact with a potential employer. A counterpart of this concept in the data is not just the formal offer received by a potential employee, but also the (informal) discussions exploring the possibility of attracting a worker which may not result in the extention of a formal offer. The probability λ_θ depends exogenously on a business cycle indicator θ and is increasing in θ. For example, a high level of θ (say, a high level of market tightness or a low level of the unemployment rate) means that it is easy to find a job, since λ_θ is high as well. Similarly, employed workers face a probability q_θ of getting a job offer, which also depends monotonically on θ. The business cycle indicator θ_t is a stochastic process which is drawn from a stationary distribution. Workers can get M offers per period, each with probability q. For simplicity, the results are first derived for the case $M = 1$ but we will show how the results need to be modified if $M > 1$ in Section 2.3. A worker who accepts the period t offer, starts working for the new employer in period $t + 1$.

Each match between worker i and a firm at date t is characterized by an idiosyncratic productivity level ϵ_t^i. Each time a worker meets a new employer, a new value of ϵ is drawn, according to a distribution function F with support $[\underline{\epsilon}, \bar{\epsilon}]$, density f and expected value μ_ϵ. For employed workers the switching rule is simple. Suppose a worker in a match with idiosyncratic productivity ϵ_t^i encounters another potential match with idiosyncratic productivity level $\tilde{\epsilon}$. We assume that the worker switches if and only if $\tilde{\epsilon} > \epsilon_t^i$, that is only if the productivity is higher in the new job than in the current one. The level of ϵ and thus productivity remain unchanged as long as the worker does not switch.[4]

In a spot wage model the period t wage depends on period t variables only, an aggregate business cycle indicator and idiosyncratic productivity. Thus, up to a log-linear approximation, each worker's wage w_t^i is a linear function of the logs of the business cycle indicator θ and idiosyncratic productivity ϵ^i,

$$\log w_t^i = \alpha \log \theta_t + \beta \log \epsilon_t^i, \tag{1}$$

where α and β are positive.[5]

To describe wages in an environment where workers can change employers and can become unemployed it is useful to follow Wolpin (1992) and partition the data for each worker into employment cycles, which last from one unemployment spell to the next one. Thus, for every worker who found a job in period 0 and has worked continuously since then we can define an employment cycle. Assume that the worker switched employers in periods $1 + T_1, 1 + T_2, \ldots 1 + T_k$, so that this worker stayed with his first employer between periods $1 = 1 + T_0$ and T_1, with the second employer between period $1 + T_1$ and T_2 and with employer j between period $1 + T_{j-1}$ and T_j. In each of these jobs the workers keep receiving offers. During job k and for $1 + T_{k-1} \leq t \leq T_k$ a worker receives N_t^k offers between period $1 + T_{k-1}$ and t. The overall number of job offers received during job k then equals $N_{T_k}^k$. The overall number of offers received since

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[4]This assumption simplifies the theoretical analysis. Adding, for example, a temporary i.i.d. productivity shock which is specific to the worker will not affect any of our conclusions.

[5]Given our assumption of no commitment, the outcome of any wage bargaining depends on the two state variables θ and ϵ only. Of course, wages in an on-the-job search model where one party has some commitment power, for example firms can commit to match outside offers, is not captured through this assumption. But this is intentional because one of our aims is to show that a model that features no commitment is consistent with the empirical evidence used to argue for the presence of wage rigidity.

the start of the employment cycle until period t is denoted N_t. For such an employment cycle and a sequence $\theta_0, \ldots, \theta_{T_j}$ of business cycle indicators, define $q_t^{HM} = q_{1+T_{j-1}} + \ldots + q_{T_j}$ and $q_t^{EH} = q_0 + \ldots + q_{T_{j-1}}$ for $1 + T_{j-1} \leq t \leq T_j$. The variable q_t^{HM} is constant within every job spell and equals the sum of q's from the start of the current job spell until the last period of this job spell. The variable q_t^{EH} summarizes the employment history in the current employment cycle until the start of the current job spell. The idea is that q^{HM} controls for selection effects from the current job spell whereas q^{EH} controls for the employment history. Note that q^{HM} and q^{EH}, the number of offers received N, and the switching dates T_j are individual specific and should have a superscript i (which we omitted for notational simplicity).

2.2   Implications

Our objective is to investigate how the expected wage of a worker who finds a job at time 0 evolves over time and how it is related to q^{HM} and q^{EH}. More precisely, we consider how the value of ϵ, one component of the wage, is related to q^{HM} and q^{EH}. The other component of the wage, $\alpha \log \theta$, is an exogenous process which affects all workers in the same way and is thus not subject to selection effects or an aggregation bias.

To simplify the exposition, we ignore the possibility of endogenous separations into unemployment. We introduce this feature into the model at the end of Section 2.3. Suppose the value of the idiosyncratic productivity level equals ϵ_{k-1} in the $(k-1)^{\text{th}}$ job before the worker switched to the kth job in period $1 + T_{k-1}$. Conditional on this we compute now the expected value of ϵ_k in this new job. The expected value of ϵ_k in period $1 + T_{k-1} \leq t \leq T_k$ for a worker who is still employed in period t and has received N_t^k offers during this job until period t equals

$$E_t(\epsilon_k | \epsilon_{k-1}, N_t^k) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \epsilon d \tilde{F}^k(\epsilon | N_t^k), \tag{2}$$

where $\tilde{F}^k(\epsilon | N_t^k) = \frac{F(\epsilon)^{1+N_t^k} - F(\epsilon_{k-1})^{1+N_t^k}}{1 - F(\epsilon_{k-1})^{1+N_t^k}}$. Note that this is the conditional expected value for a worker who is still employed and has not been displaced exogenously. Every time there is a contact between the worker and a firm a new value of ϵ is drawn from the exogenous distribution F. The probability that a worker in a match with idyosincratic productivity $\hat{\epsilon}$ declines such an offer equals $F(\hat{\epsilon})$. The probability to decline N_t^k offers then equals $F(\hat{\epsilon})^{N_t^k}$. To

derive the distribution of ϵ, we have to take into account that the worker switched implying that $\epsilon_k \geq \epsilon_{k-1}$. The distribution has then to be truncated at ϵ_{k-1} and has to be adjusted to make it a probability mass, which results in $\tilde{F}^k(\epsilon|N_t^k)$.[6] This distribution, indexed by the number of offers received, is ranked by First-order-stochastic dominance. Thus, a higher number of offers N_t^k leads to a higher expected value of ϵ. The reason is that a worker with more offers rejected more offers which indicates that he drew a higher ϵ at the beginning of the current job.

The best predictor of ϵ_t, using the information available at date t, equals

$$E_t(\epsilon_k|\epsilon_{k-1}, N_t^k) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \epsilon \, d\tilde{F}^k(\epsilon \mid N_t^k). \tag{3}$$

Since ϵ_τ is constant for $1 + T_{k-1} \leq \tau \leq T_k$, we use the predictor which contains the most information about this ϵ, the expectation at T_k. The expectation of ϵ_k at $1 + T_{k-1} \leq t \leq T_k$ then equals

$$E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \epsilon \, d\tilde{F}^k(\epsilon \mid N_{T_k}^k). \tag{4}$$

Taking expectations w.r.t. $N_{T_k}^k$ then yields the expectation of ϵ_k, conditional on ϵ_{k-1}

$$E_t(\epsilon_k|\epsilon_{k-1}) = \sum_{N_{T_k}^k} E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) P_{T_k}^k(N_{T_k}^k), \tag{5}$$

where $P_{T_k}^k(N_{T_k}^k)$ is the probability of having received $N_{T_k}^k$ offers in job k (from period $1 + T_{k-1}$ to period T_k).

2.3 Linearization

To make our estimator $E_t(\epsilon_k|\epsilon_{k-1})$ applicable for our empirical implementation, we linearize (5) and relate it to an observable (to the econometrician) variable. We first approximate the integral (4). It equals (integration by parts):

$$E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) = \bar{\epsilon} - \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \frac{F(\epsilon)^{1+N_{T_k}^k} - F(\epsilon_{k-1})^{1+N_{T_k}^k}}{1 - F(\epsilon_{k-1})^{1+N_{T_k}^k}} d\epsilon \,. \tag{6}$$

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[6]The precise derivation of $\tilde{F}^k(\epsilon|N_t^k)$ can be found in Appendix I.1.

Linearization of this expression w.r.t. $N_{T_k}^k$ and ϵ_{k-1} around a steady state where all variables are evaluated at their expected values in a steady state yields

$$E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) \approx c_0 + c_1 N_{T_k}^k + c_2\epsilon_{k-1}, \tag{7}$$

where the coefficients c_1 and c_2 are the first derivatives, which are shown to be positive in Appendix I.2.

The expected value of ϵ_k conditional on ϵ_{k-1}, $E_t(\epsilon_k|\epsilon_{k-1})$ can then be simplified to:[7]

$$E_t(\epsilon_k|\epsilon_{k-1}) \approx c_0 + c_1 \sum_{N_{T_k}^k} N_{T_k}^k P_{T_k}(N_{T_k}^k) + c_2\epsilon_{k-1}. \tag{8}$$

The expected number of offers in period t equals q_t since every worker receives one offer with probability q_t and no offer with probability $1 - q_t$. Since taking expectations is additive - the sum of expectations equals the expectation of the sum - the expected value of ϵ_k, conditional on ϵ_{k-1} for $1 + T_{k-1} \leq t \leq T_k$ can be expressed as

$$E_t(\epsilon_k \mid \epsilon_{k-1}) \approx c_0 + c_1 \sum_{\tau=1+T_{k-1}}^{T_k} q_\tau + c_2\epsilon_{k-1} = c_0 + c_1 q_{T_k}^{HM} + c_2\epsilon_{k-1}. \tag{9}$$

It thus holds for the unconditional expectation

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2 E_{T_{k-1}}(\epsilon_{k-1}). \tag{10}$$

We have thus established that the expected value of ϵ is a function of q^{HM}.

To relate $E_{T_{k-1}}(\epsilon_{k-1})$ to the worker's employment history before the current job started, we approximate $E_{T_{k-1}}(\epsilon_{k-1})$ by applying the derivation for ϵ_k to ϵ_{k-1}. This yields, analogously to equation (10), the expected value of $E_t(\epsilon_{k-1})$, for $1 + T_{k-2} \leq t \leq T_{k-1}$:

$$E_t(\epsilon_{k-1}) \approx c_0 + c_1 q_{T_{k-1}}^{HM} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) \tag{11}$$

so that for $1 + T_{k-1} \leq t \leq T_k$

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2\{c_0 + c_1 q_{T_{k-1}}^{HM} + c_2 E_{T_{k-2}}(\epsilon_{k-2})\}.$$

Iterating these substitutions for $\epsilon_{k-2}, \epsilon_{k-3}, \ldots$ shows that for any $0 \leq m \leq k-1$, $E_t(\epsilon_k)$ can be approximated as a function of $q_{T_k}^{HM}, \ldots q_{T_{k-m}}^{HM}$ and $E_{T_{k-m-1}}(\epsilon_{k-m-1})$. However, this procedure

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[7]Note that the expectation w.r.t. N_{T_k} only affects the N-term since ϵ_{k-1} is constant in job spell k.

inflates the number of regressors and we will find that this renders many of them insignificant. We therefore truncate this iteration at some point and capture the employment history by just one variable. To approximate $E_{T_{k-1}}(\epsilon_{k-1})$ for a worker in job k, assume that he has received $N_{T_{k-1}}$ offers during the current employment cycle before he started job k. The probability for such a worker to have a value of ϵ less than or equal to $\hat{\epsilon}$ equals

$$Prob(\epsilon \le \hat{\epsilon}) = F(\hat{\epsilon})^{1+N_{T_{k-1}}}, \tag{12}$$

The same arguments as above establish that

$$E_{T_{k-1}}(\epsilon_{k-1}) = \sum_{N_{T_{k-1}}} E_{T_{k-1}}(\epsilon_{k-1} \mid N_{T_{k-1}})P_{T_{k-1}}(N_{T_{k-1}}), \tag{13}$$

where $P_{T_{k-1}}(N_{T_{k-1}})$ is the probability of having received $N_{T_{k-1}}$ offers up to period T_{k-1}. Furthermore, the same linearization as before of

$$E_{T_{k-1}}(\epsilon_{k-1}|N_{T_{k-1}}) = \bar{\epsilon} - \int_{\underline{\epsilon}}^{\bar{\epsilon}} F(\epsilon)^{1+N_{T_{k-1}}} d\epsilon \tag{14}$$

yields

$$E_{T_{k-1}}(\epsilon_{k-1}) \approx c_3 + c_4 q_{T_{k-1}}^{EH}. \tag{15}$$

Using this approximation in (10) yields

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2(c_3 + c_4 q_{T_{k-1}}^{EH}). \tag{16}$$

We can also apply this truncation to approximate $E_{T_{k-m}}(\epsilon_{k-m})$ through $q_{T_{k-m}}^{EH}$ for any $0 \le m \le k-1$, so that $E_t(\epsilon_{k-m})$ can be approximated as a function of $q_{T_k}^{HM}, \ldots q_{T_{k-m}}^{HM}$ and $q_{T_{k-m-1}}^{EH}$. In our benchmark we use only two regressors $q_{T_k}^{HM}$ and $q_{T_{k-1}}^{EH}$ as implied by equation (16) and show that this parsimonious specification yields the same results as richer specifications which use more regressors.

Finally, we approximate

$$\log(\epsilon) \approx \tilde{c}_0 + \tilde{c}_1 \log(q^{HM}) + \tilde{c}_2 \log(q^{EH}), \tag{17}$$

for coefficients $\tilde{c}_i$.

The analysis above was based on the assumption that we, as econometricians, observe all the relevant information but this might be too optimistic. At least two simple scenarios

are conceivable where this is not the case. First, there could be a standard time aggregation problem. Every period in the data observed by the econometrician contains M model periods. An example would be that the data are monthly but that a worker can receive an offer in every of the four weeks of the month, so that $M = 4$ in this case. If $q_1, \ldots, q_M$ are the probabilities of receiving an offer during such an observational period, then the expected number of offers equals $q_1 + \ldots + q_M$, or in the special case if $q_i = q$ is constant it equals qM. The econometrician observes the average value of q_i during this period, $\hat{q} = \frac{q_1 + \ldots + q_M}{M}$, and computes the expected number of offers to be equal to $\hat{q}M = q_1 + \ldots + q_M$. Thus all our derivations remain unchanged since $\hat{q}$ differs from the model implied regressor $q_1 + \ldots + q_M$ just by the multiplicative constant M, which drops out since we take logs. Similar arguments apply to the second scenario. Suppose the date a worker receives an offer and his first day in the new job are separated in time. In this case a worker who received an offer in week one to start a job at the beginning of the next month may change his mind and accept a better offer received, say, in week three. More generally, the worker could just collect the M offers received within a month and then accept the best one and start working in this job next month. As in the first scenario we again obtain an unbiased estimate of the expected number of offers, $q_1 + \ldots + q_M$.

So far we have assumed that all matches dissolve exogenously. This ignores another potentially important selection effect incorporated in many search models (Mortensen and Pissarides (1994)). Matches get destroyed if their quality falls below a threshold (which can change over time). To capture endogenous separations, we assume that at any point of time all matches with a value of ϵ below σ_t break up or do not get created. If the match is not productive enough, ϵ is too low, the match is dissolved. The exact cut-off level σ_t depends on our business cycle indicator θ_t. The cut-off level σ_t is decreasing in θ_t. If θ is high matches with a lower value of ϵ get destroyed than when θ is low.[8] If $\sigma_t \leq \underline{\epsilon}$, unemployed workers accept all offers.

We show in Appendix I.3 that allowing for endogenous separations leads to the following

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[8]This is the standard assumption that recessions feature the Schumpeterian "cleansing" effect which is well supported by the empirical evidence and is featured by many theoretical models (see, e.g., Barlevy (2002), Gomes, Greenwood, and Rebelo (2001)). This assumption is also consistent with evidence of a substantial cyclical composition bias in, e.g., Solon, Barsky, and Parker (1994) who find that low-skill workers, who tend to occupy the less productive matches are employed in booms but not in recessions.

modification of our approximation

$$\log(\epsilon_k) \approx \tilde{c}_0 + \tilde{c}_1 \log(q_{T_k}^{HM}) + \tilde{c}_2 \log(q_{T_{k-1}}^{EH}) + \tilde{c}_3 \log(\tilde{\sigma}_k^{max}) + \tilde{c}_4 \log(\Sigma_{k-1}^{max}), \qquad (18)$$

where $\Sigma_{k-1}^{max} = \max\{\sigma_0, \ldots, \sigma_{T_{k-1}}\}$ is the highest value of σ before the current job started. This variable captures the potential selection through endogenous separations the worker has experienced before the current job k started. A high individual level of Σ_{k-1}^{max} implies that the worker's previous job matches in the current employment cycle have survived bad times and thus are likely to be of high quality. To capture selection through endogenous separations in the current job, we define $\sigma_t^k := \max\{\sigma_{1+T_{k-1}}, \ldots, \sigma_t\}$ for $1 + T_{k-1} \leq t \leq T_k$ and $\sigma_k^{max} = \sigma_{T_k}^k$. Furthermore we define an indicator $\mathcal{I}$ which equals one if $\sigma_k^{max} > \Sigma_{k-1}^{max}$ and equals zero if $\sigma_k^{max} < \Sigma_{k-1}^{max}$. We then show that $\tilde{\sigma}_k^{max} = \mathcal{I}_{\sigma_k^{max} > \Sigma_{k-1}^{max}} \sigma_k^{max}$ controls for endogenous separations in the current job. The argument has two parts. First, surviving a higher value of σ_k^{max} implies that the worker's match quality is likely to be high. Second, however, this argument has bite only if $\sigma_k^{max} > \Sigma_{k-1}^{max}$. If instead $\sigma_k^{max} \leq \Sigma_{k-1}^{max}$ and $\epsilon < \sigma_k^{max}$ job k would not survive. But the worker would not have made it to job k since $\epsilon < \Sigma_{k-1}^{max}$; he was already separated earlier.

3   Applications

In this section, we show theoretically that our search model can rationalize several findings in the literature, which have been interpreted as evidence against models with spot wages. Since our spot wages model - the wage in period t is a function of a current business cycle indicator and idiosyncratic productivity in period t only - generates the same history dependence, such evidence needs further investigation. We address this in the empirical part of the paper.

3.1   History Dependence in Wages

If the unemployment rate is the business cycle indicator, as is commonly assumed in empirical applications, and the labor market is characterized through spot wages, then the current unemployment rate and not any function of the history of unemployment rates should be an important determinant of wages. However, in the data, the current wage is found to depend on variables such as the lowest unemployment rate, u^{min}, or the unemployment rate at the start of the job, u^{begin}. We now show that these relationships hold in our model as well if there is

sufficient positive co-movement (defined below) of the business cycle indicator over time. We first establish these results for a different business cycle indicator, q. For this indicator, the relevant variables are $q^{max} = \max\{q_{1+T_{i-1}}, \ldots q_{T_i}\}$, corresponding to u^{min}, and $q^{begin} = q_{1+T_{i-1}}$, corresponding to u^{begin}. The result for the unemployment rate is then a consequence of a strong negative correlation between q and u.

Sufficient co-movement of the process q is defined as follows. Let $H_{r,t}$ be the cdf of q_r conditional on q_t for some periods r and t. We then require that $\frac{H_{r,t}(q_r|q_t)}{H_{r,t}(q_t|q_t)}$ is increasing in q_t. This assumption would for example follow if q_t shifts the distribution $H_{r,t}$ by first-order stochastic dominance ($H_{r,t}(q_r \mid q_t)$ is decreasing in q_t) and if $H_{r,t}(q_t \mid q_t)$ is increasing in q_t. Sufficient co-movement then implies that $E[q_r \mid q_t \geq q_r]$ is increasing in q_t.[9] Note that a standard AR(1) process fulfills this assumption.[10] We now show that under this assumption the wage is also increasing in $q^{max} = \max\{q_{1+T_{i-1}}, \ldots q_{T_i}\}$. Specifically we show that $E[q_{T_i}^{HM} \mid q^{max} = \bar{q}]$ is an increasing function of $\bar{q}$. It holds that

$$E[q_{T_i}^{HM} \mid q^{max} = \bar{q}] = \sum_{t=1+T_{i-1}}^{T_i} E[q_{T_i}^{HM} \mid q^{max} = q_t = \bar{q}] Prob(q^{max} = q_t \mid q^{max} = \bar{q}). \qquad (19)$$

Since q_t is a realization from a stationary distribution, the probability that the highest value of q is realized in a specific period is the same for every period. In particular, the probability that $q^{max} = q_t$ is independent from $\bar{q}$, $Prob(q^{max} = q_t \mid q^{max} = \bar{q}) = Prob(q^{max} = q_t)$.

Since our assumption of sufficient co-movement implies that $E[q_{T_i}^{HM} \mid q^{max} = q_t = \bar{q}]$ is increasing in $q_t = \bar{q}$, $E[q_{T_i}^{HM} \mid q^{max} = \bar{q}]$ is increasing in $\bar{q}$ as well. Thus we have shown that in our model wages are increasing in q^{max}. If q^{max} and the lowest unemployment rate during a job spell, $u^{min} = \min\{u_{1+T_{i-1}}, \ldots u_{T_i}\}$, are negatively correlated (what clearly holds in the data) wages are decreasing in u^{min}.

Thus we have established that our model can replicate the finding that the current wage depends on the lowest unemployment rate during the current job spell although the wage only

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[9]Partial integration shows that $E[q_r \mid q_t \geq q_r] = q_t - \int_{\underline{q}}^{q_t} \frac{H_{r,t}(q_r|q_t)}{H_{r,t}(q_t|q_t)} dq_r$, where $\underline{q}$ is the lowest possible realization of q. Under our assumptions this expectation is increasing in q_t.

[10]If q follows an AR(1) process and $r > t$, it holds that $q_r = \rho q_t + \eta$, for some number $1 > \rho > 0$ and some error term η. In this case $H_{r,t}(q_r \mid q_t) = Prob(\eta \leq q_r - \rho q_t)$ is decreasing in q_t and $H_{r,t}(q_t \mid q_t) = Prob(\eta \leq (1-\rho)q_t)$ is increasing in q_t. If $r < t$, $q_r = (1/\rho)(q_t - \eta)$ (just invert the equation above). In this case $H_{r,t}(q_r \mid q_t) = Prob(\eta \geq q_t - \rho q_r)$ is decreasing in q_t and $H_{r,t}(q_t \mid q_t) = Prob(\eta \geq (1-\rho)q_t)$ is increasing in q_t.

depends on the current unemployment rate and idiosyncratic productivity. The variable u^{min} is negatively correlated with the idiosyncratic productivity component ϵ. As long as one does not control for this unobserved productivity component, other variables, such as u^{min} or q^{max} will proxy for it and and as a consequence affect wages even in the absence of any built-in history dependence.

The reasoning for the persistent effects of recessions is identical. In this case the unemployment rate at the beginning of an employment spell has a negative effect on wages in later periods. This also holds in our model if the idiosyncratic component is not appropriately controlled for. The argument is exactly the same as the one we gave for the minimum unemployment rate, u^{min}.

The finding that the current wage depends on u^{min} or u^{begin} is usually interpreted as evidence for implicit contracting models, which do not lead to inefficient separations. The logic is as follows. Suppose a risk-neutral firm and a risk averse worker sign a contract. If both parties can commit to fulfill the contract, the firm pays the worker a constant wage independent of business cycle conditions. In this case the current wage is a function of the unemployment rate at the beginning of the current job spell only. If however, the worker cannot commit to honor the contract, such a constant wage cannot be implemented. If business cycle conditions improve, the worker can credibly threat to take another higher paying job. The contract is then renegotiated to yield a higher constant wage which prevents the worker from leaving. Such an upward adjustment of the wage occurs whenever outside labor market conditions are better than they were when the current contract was agreed to. As a result, the best labor market conditions during the current job spell determine the current wage. If the unemployment rate is the business cycle indicator, as is commonly assumed, then the lowest unemployment rate, u^{min}, determines the wage. If workers cannot credibly threat to leave their current employer, for example because of high mobility costs, then the contract is never renegotiated and the business cycle conditions at the start of the job determine the wage. If firms are risk-neutral then the wage is a function of u^{min} or, in case of no mobility, u^{begin} (the unemployment rate at the start of the job) only. If firms are also risk-averse, then the risk is shared between the worker and the firm and the current wage also depends on the current unemployment rate. Depending on the assumption on mobility, the wage is still either a function of u^{min} or u^{begin}.

The only difference to risk neutrality is that the wage is not only a function of u^{min} or u^{begin} but also depends on the current unemployment rate. Our empirical results will show that the existing evidence for these types of contracts becomes insignificant once we control for selection effects.

3.2 Wage Volatility of Job Stayers and Switchers

In this section we consider the cyclical behavior of wages for workers who stayed with their current employer and for those who start with a new employer, either because they switched job-to-job or because they were not employed and found a new job. We consider how the wages of stayers and switchers change with business cycle conditions, again parameterized through the variable q. Since the wage is determined by aggregate conditions which are the same to everyone, whether switcher or not, and idiosyncratic productivity that differs across matches, we focus on the idiosyncratic productivity component ϵ. If the expected value of ϵ is higher for one group of workers, the expected wage is also higher for this group.

For a stayer such a comparison is simple as he holds the same job today as he did last period. As a result his value of ϵ is the same in both periods, independent of the business cycle conditions:

$$\Delta_t^{stayer} = \epsilon_t - \epsilon_{t-1} = 0. \tag{20}$$

We now show that this does not hold for switchers. We consider a switcher who has received N offers during the current employment cycle, so that his ϵ is distributed according to F^N before he switches. This parametrization through N captures both newly hired workers who left unemployment ($N = 0$) and job-to-job switchers ($N \geq 1$). We compute the average ϵ as a function of q, our business cycle indicator. Each worker can get at most M offers each with success probability q. Since we consider someone who just switched, we know that he has received at least one offer. The probability that a switcher has received $k \in \{1, 2, \ldots, M\}$ offers is

$$\frac{k}{N+k} \frac{\binom{M}{k} q^k (1-q)^{M-k}}{\sum_l \frac{l \binom{M}{l} q^l (1-q)^{M-l}}{N+l}} \tag{21}$$

Since the distribution of ϵ is described by F^k for someone who has received k offers, the

distribution of ϵ for a switcher equals

$$\sum_{k=1}^{M} F(\epsilon)^{N+k} \frac{k}{N+k} \frac{\binom{M}{k} q^k (1-q)^{M-k}}{\sum_l \frac{l \binom{M}{l} q^l (1-q)^{M-l}}{N+l}}. \tag{22}$$

Appendix I.4 establishes that an increase in q shifts this distribution by first-order stochastic dominance and thus that the expected value of ϵ is increasing in q. Since a higher value of q reflects better business cycle conditions, this result says that the wages of switchers are higher in a boom than in a recession. In particular, their responsiveness to q or unemployment is larger than the responsiveness of stayers' wages, which is zero. Thus the model implies that wages of switchers are more volatile than wages of job stayers.

4   Empirical Methodology

4.1   Implicit Contracts and the Persistent Effects of Recessions

We use data from the National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID). We will replicate the findings of Beaudry and DiNardo (1991) on each of the two data sets and then contrast them with the specification implied by our model.

The following regression equation forms the basis of the empirical investigation in Beaudry and DiNardo (1991):

$$ln\ w(i,\, t+j,\, t) = X_{i,t+j}\ \Omega_1 + \Omega_2\ U_{t+j} + \epsilon_{i,t+j}. \tag{23}$$

That is, the wage in period $t+j$ for an individual i who began the job in period t is a function of his individual characteristics X_i, the aggregate labor market conditions summarized by the current unemployment rate U_{t+j} and an error term $\epsilon_{i,t+j}$. The error term is assumed to include a permanent individual-specific component. As in Beaudry and DiNardo (1991), we include individual fixed effects in equation (23) to control for permanent unobserved individual attributes that affect wages. The vector of controls, X, used for estimation includes a quadratic in age, tenure, experience, and years of education, as well as dummies for industry, region, race, union status, marriage, and standard metropolitan statistical area (SMSA). These dummy variable are included for comparability with the existing literature. Since they

are not necessarily implied by the theory we verified that all of our results are robust to excluding any or all of these dummy variables. The quadratic specification for tenure might be restrictive. The reason is that if the specification does not allow for enough curvature in tenure, the minimum unemployment rate since the start of the job or q^{HM} and q^{EH} might proxy for the true returns to tenure. We adopt the quadratic specification only for comparability with the literature. Otherwise we would have chosen a specification with at least a cubic in tenure as the benchmark. All of our results are robust, however, to allowing for more curvature in tenure.

To test for the presence of implicit contracts to which firms and workers can credibly commit, Beaudry and DiNardo (1991) add the unemployment rate at the start of the current job $u^{begin} := U_t$ to the set of regressors in equation (23) and find that the estimated coefficient on this variable is significantly different from zero. To test for the presence of implicit contract to which firms can commit but workers cannot, they add the minimum unemployment rate since the start of the current job $u^{min} := min\{U_{t-k}\}_{k=0}^{j}$ to the set of regressors in equation (23) and find that the estimated coefficient on u^{min} is significantly different from zero as well.

However, the derivations above establish that these results are also qualitatively consistent with the on-the-job search model with spot wage determination. This is so because, e.g., the minimum unemployment rate variable is correlated with (is an imperfect proxy for) q^{HM} and q^{EH}. A simple and natural way to tell these models apart is to include q^{HM} and q^{EH} into the set of regressors. If the minimum unemployment variable remains significant, it would imply that it contains some independent information and might indicate empirical support for the rigid wage model. If it becomes insignificant in the presence of the variables implied by the on-the-job search model, one would conclude that the spot wage model is consistent with the data instead. This is the experiment we perform. Assessing the persistent effects of recessions is identical to this analysis with the only difference that we substitute u^{min} through u^{begin}.

4.2   Wage Volatility of Job Stayers and Switchers

The objective of this section is to describe how we measure the volatility of wages over the business cycle for job stayers and switchers. The l'th employment cycle starts in period t_l^U (when the worker leaves unmployment), ends in period t_l^E (when the worker becomes unemployed)

and the worker starts new jobs in periods $t_{l,1}^J, \ldots t_{l,s_l}^J$ (without going through unemployment). The employment cycle is then described through the vector

$$c_l = (t_l^U, t_{l,1}^J, t_{l,2}^J, \ldots t_{l,s_l}^J, t_l^E), \tag{24}$$

and the full work history is described through the sequence of all employment cycles

$$c = (c_1, c_2, \ldots, c_L). \tag{25}$$

To measure the volatility of wages for stayers, new hires and job-to-job movers in the data we have to be aware of unobserved individual heterogeneity. A standard cure for this problem is to first-difference the data. For job stayers this idea is straightforward to implement. A worker in period t is a job stayer if he was employed in the same job in period $t-1$. That means that there is an employment cycle l such that $t_l^U \leq t \leq t_l^E$ and and t is neither the first period of this cycle, $t \neq t_l^U$, nor a period where the worker switched, $t \notin \{t_{l,1}^J, t_{l,2}^J, \ldots t_{l,s_l}^J\}$. To measure the response of stayers' wages to unemployment rates we then regress the change in the log wage between two consecutive observations on the change in the unemployment rate:

$$log(w_t) - log(w_{t-1}) = \beta^S(u_t - u_{t-1}) + \text{change in controls (tenure, etc.)} + \text{error term.} \tag{26}$$

The estimated value β^S describes the responsiveness of wages to changes in unemployment for stayers.

For new hires we do something similar to measure their wage volatility. We consider how the wage in the first period of an employment cycle depends on the unemployment rate for the same individual. Using only these observations gives us a sequence of wages $(w_{t_1^U}, \ldots, w_{t_L^U})$ and corresponding unemployment rates $(u_{t_1^U}, \ldots, u_{t_L^U})$. First differencing these data results in the regression

$$log(w_{t_i^U}) - log(w_{t_{i-1}^U}) = \beta^U(u_{t_i^U} - u_{t_{i-1}^U}) + \text{change in controls} + \text{error term,} \tag{27}$$

where β^U describes the responsiveness of wages to changes in unemployment for new hires. Restricting to the same individual finding a job at different points in time allows us to control for individual fixed effects. Note that the data used to run this regression necessarily only includes those individuals who left unemployment at least twice.

For job-to-job switchers we proceed similarly. Again we measure the responsiveness of wages for a worker who switched jobs at different points in time. This gives a wage series $(w_{t_{1,1}^J}, \ldots, w_{t_{1,s_1}^J}, w_{t_{2,1}^J}, \ldots, w_{t_{2,s_2}^J}, \ldots, w_{t_{L,1}^J}, \ldots, w_{t_{L,s_L}^J})$ comprising the wages in all periods when the worker changes employers. We again regress the change in the log wage between two such consecutive observations on the corresponding change in the unemployment rate:

$$log(w_{t_{l,s}^J}) - log(w_{w_{t_{l,s-1}^J}}) = \beta^J (u_{t_{l,s}^J} - u_{t_{l,s-1}^J}) + \text{change in controls} + \text{error term}, \qquad (28)$$

where we define $t_{l,0}^J = t_{l-1,s_{l-1}}^J$. The estimated value β^J then describes the responsiveness of wages to changes in unemployment for job-to-job switchers.

5   Empirical Evidence

The primary data set on which our empirical analysis is based is the National Longitudinal Survey of Youth described in detail below. NLSY is convenient because it allows to measure all the variables we are interested in. In particular, it contains detailed work-history data on its respondents in which we can track employment cycles.

Our conclusions also hold on the Panel Study of Income Dynamics data – the dataset originally used by Beaudry and DiNardo (1991). Unfortunately, PSID does not permit the construction of q^{EH} because unemployment data is not available in some of the years making it impossible to construct histories of job spells uninterrupted by unemployment. Thus, we are only able to include q^{HM} into the regressions run on the PSID data. Because of this limitation the results based on the PSID are delegated to Appendix III.

5.1   National Longitudinal Survey of Youth Data

The NLSY79 is a nationally representative sample of young men and women who were 14 to 22 years of age when first surveyed in 1979. We use the data up to 2006. Each year through 1994 and every second year afterward, respondents were asked questions about all the jobs they held since their previous interview, including starting and stopping dates, the wage paid, and the reason for leaving each job.

The NLSY consists of three subsamples: A cross-sectional sample of 6,111 youths designed to be representative of noninstitutionalized civilian youths living in the United States in 1979

and born between January 1, 1957, and December 31, 1964; a supplemental sample designed to oversample civilian Hispanic, black, and economically disadvantaged nonblack/non-Hispanic youths; and a military sample designed to represent the youths enlisted in the active military forces as of September 30, 1978. Since many members of supplemental and military samples were dropped from the NLSY over time due to funding constraints, we restrict our sample to members of the representative cross-sectional sample throughout.

We construct a complete work history for each individual by utilizing information on starting and stopping dates of all jobs the individual reports working at and linking jobs across interviews. In each week the individual is in the sample we identify the main job as the job with the highest hours and concentrate our analysis on it. Hours information is missing in some interviews in which case we impute it if hours are reported for the same job at other interviews. We ignore jobs that in which individual works for less than 15 hours per week or that last for less than 4 weeks.[11]

We partition all jobs into employment cycles following the procedure in Barlevy (2008). We identify the end of an employment cycle with an involuntary termination of a job. In particular, we consider whether the worker reported being laid off from his job (as opposed to quitting). We use the workers stated reason for leaving his job as long as he starts his next job within 8 weeks of when his previous job ended, but treat him as an involuntary job changer regardless of his stated reason if he does not start his next job until more than 8 weeks later.[12] If the worker offers no reason for leaving his job, we classify his job change as voluntary if

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[11]We have also experimented with the following more complicated algorithm with no impact on our conclusions. (1) Hours between all the jobs held in a given week are compared and the job with the highest hours is assigned as the main job for that week. (2) If a worker has the main job A, takes up a concurrent job B for a short period of time, then leaves job B and continues with the original main job A, we ignore job B and consider job A to be the main one throughout (regardless of how many hours the person works in job B). (3) If a worker has the main job A, takes up a concurrent job B, then leaves job A and continues with job B, we assign job B to be the primary one during the period the two jobs overlap (regardless of how many hours the person works in job B).

[12]As Barlevy (2008) notes, most workers who report a layoff do spend at least one week without a job, and most workers who move directly into their next job report quitting their job rather than being laid off. However, nearly half of all workers who report quitting do not start their next job for weeks or even months. Some of these delays may be planned. Yet in many of these instances the worker probably resumed searching from scratch after quitting, e.g. because he quit to avoid being laid off or he was not willing to admit he was laid off.

he starts his next job within 8 weeks and involuntary if he starts it after 8 weeks. We ignore employment cycles that began before the NLSY respondents were first interviewed in 1979.

At each interview the information is recorded for each job held since the last interview on average hours, wages, industry, occupation, etc. Thus, we do not have information on, e.g., wage changes in a given job during the time between the two interviews. This leads us to define the unit of analysis, or an observation, as an intersection of jobs and interviews. A new observation starts when a worker either starts a new job or is interviewed by the NLSY and ends when the job ends or at the next interview, whichever event happens first. Thus, if an entire job falls in between of two consecutive interviews, it constitutes an observation. If an interview falls during a job, we will have two observations for that job: the one between the previous interview and the current one, and the one between the current interview and the next one (during which the information on the second observation would be collected). Consecutive observations on the same job broken up by the interviews will identify the wage changes for job-stayers. Following Barlevy (2008), we removed observations with an reported hourly wage less than or equal to $0.10 or greater than or equal to $1,000. Many of these outliers appear to be coding errors, since they are out of line with what the same workers report at other dates, including on the same job.

To each observation we assign a unique value of worker's job tenure, labor market experience, race, marital status, education, smsa status, and region of residence, and whether the job is unionized. Since the underlying data is weekly, the unique value for each of these variables in each observation is the mode of the underlying variable (the mean for tenure and experience) across all weeks corresponding to that observation. The educational attainment variable is forced to be non-decreasing over time.

We merge the individual data from the NLSY with the aggregate data on unemployment, vacancies and employed workers' separations rates. Seasonally adjusted unemployment, u, is constructed by the Bureau of Labor Statistics (BLS) from the Current Population Survey (CPS). The seasonally adjusted help-wanted advertising index, v, is constructed by the Conference Board. Both u and v are quarterly averages of monthly series. The ratio of v to u is the measure of the labor market tightness. Quarterly employed workers' separation rates were

constructed by Robert Shimer.[13]

We use the underlying weekly data for each observation (job-interview intersection) to construct aggregate statistics corresponding to that observation. The current unemployment rate for a given observation is the average unemployment rate over all the weeks corresponding to that observation. Unemployment at the start of the job is the unemployment rate in the week the job started. It is naturally constant across all observations corresponding to a job. Next, we go week by week from the beginning of the job to define the lowest unemployment since the start of the job in each of those weeks to be equal to the lowest value the unemployment rate took between the first week in the job and the current week. The minimum unemployment rate since the start of the job for a given observation is then the average of the sequence of weekly observations on minimum unemployment across all weeks corresponding to that observation.

Finally, we add up the values of market tightness in each week of each observation in each job since the beginning of the current employment cycle until the beginning of the current job to define q^{EH}. All observations in the current job are then assigned this value. The sum of weekly market tightnesses across all weeks corresponding to all observations in a job yield the value of q^{HM} for that job (and each observation in it). The highest employed workers' separation rate across all weeks of all observations in all jobs since the beginning of the current employment cycle until the beginning of the current job determines Σ^{max}. All observations in the current job are assigned this value. The highest separation rate across all weeks corresponding to all observations in a job yields the value of σ^{max} for that job (and each observation in it).

All empirical experiments that we conduct are based on the individual data weighted using custom weights provided by the NLSY which adjust both for the complex survey design and for using data from multiple surveys over our sample period. In practice, we found that using weighted or unweighted data has no impact on our substantive findings.

5.2 Empirical Results

Columns 1 and 2 of Table 1 indicate that wages of the relatively young workers in the NLSY are strongly procyclical, even after the procyclical sorting into better matches is controlled

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[13]For details, please see Shimer (2007) and his webpage http://robert.shimer.googlepages.com/flows.

for.[14]

Column 3 replicates the main result in Beaudry and DiNardo (1991). When the minimum unemployment rate since the start of the job is included in the regression, it has a strong impact on wages. This effect of past labor market conditions is so important that, when it is accounted for, current unemployment has no significant impact on wages.

When we add the q^{HM} and q^{EH} regressors that control for selection in the on-the-job search model in Column 4 we find that the effect of the minimum unemployment on wages becomes insignificant, while the effect of the current unemployment rate is nearly as strong as in the regression that does not include minimum unemployment. This column provides a direct test of the two competing explanations for the history dependence in wages. The results suggest that it arises not because of the presence of implicit contracts, but because the expected wage depends on the number of offers received during the current job and before the current job started.

Similar conclusions follow from the results in Columns 5 and 6 that add the unemployment rate at the start of the job to the set of regressors. When the expected number of offers is not included in the regression, this regressor is a significant determinant of wages. When selection is accounted for, however, its effect becomes insignificant.

The regressors that control for match qualities in our model were derived using a linear approximation. Higher order approximations would imply that interactions between q^{HM} and q^{EH} might also help in predicting match qualities. We can evaluate whether this is the case by including a product of q^{HM} and q^{EH} among the regressors in the model. We find that the estimated coefficient on this interaction term is highly statistically insignificant and that the presence of this term in the regression does not affect other estimated coefficients.[15]

Table 2 shows that neither our results nor those of Beaudry and DiNardo (1991) are driven by the restrictive curvature specification for the returns to tenure and experience. Instead of the quadratic specification in the benchmark, the estimates reported in this table are based on a regression that includes a full set of annual tenure and experience dummies. The results are very similar to those in Table 1 and we continue with the benchmark specification in the

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[14]The tables contain only the estimated coefficients on the variables of interest. All the regressions contain the full list of variables described in Section 4.1.

[15]We omit presenting a table with the results of this experiment.

rest of the analysis.[16]

In Table 3, we control, as suggested by the theory, for endogenous separations through including the regressors $\tilde{\sigma}^{max}$ and Σ^{max}. Controlling for endogenous separations has very little impact on our main findings. Across various specifications, we find that $\tilde{\sigma}^{max}$ is never significant, while its lagged values are significant and positive but do not noticeably affect the estimated coefficients of u, u^{min}, u^{begin}, q^{HM} and q^{EH}.[17]

In Table 4 we report the results based on the expanded set of regressor included to control for selection. The results described above were based on our parsimonious specifications that only included q^{HM} (and $\tilde{\sigma}^{max}$) to measure the selection effects in the current job, and q^{EH} (and Σ^{max}) to measure the selection effects revealed by previous jobs during the current employment cycle. The theory developed in Section 2 allows for more regressors. We showed that for any $0 \leq m \leq k-1$, $E_t(\epsilon_k)$ can be approximated as a function of $q^{HM}_{T_k}, \ldots q^{HM}_{T_{k-m}}, q^{EH}_{T_{k-m-1}}$ and $\tilde{\sigma}^{max}_k, \tilde{\sigma}^{max}_{k-1}, \ldots \tilde{\sigma}^{max}_{k-m}$ and Σ^{max}_{k-m-1}. The case $m=0$ corresponds to our parsimonious specification, in case $m=1$, we include $q^{HM}_{T_k}, q^{HM}_{T_{k-1}}, q^{EH}_{T_{k-2}}, \tilde{\sigma}^{max}_k, \tilde{\sigma}^{max}_{k-1}$ and Σ^{max}_{k-2}, in case $m=2$ we include $q^{HM}_{T_k}, q^{HM}_{T_{k-1}}, q^{HM}_{T_{k-2}}, q^{EH}_{T_{k-3}}, \tilde{\sigma}^{max}_k, \tilde{\sigma}^{max}_{k-1}, \tilde{\sigma}^{max}_{k-2}$ and Σ^{max}_{k-3}, and so on. Table 4 contains the results for $m=1$ and $m=2$ where we denote $q^{HM}_{T_{k-m}}$ by q^{HM}_{-m}, $q^{EH}_{T_{k-m-1}}$ by q^{EH}_{-m}, $\tilde{\sigma}^{max}_{k-m}$ by $\tilde{\sigma}^{max}_{-m}$ and Σ^{max}_{k-m-1} by Σ^{max}_{-m}. Our substantive conclusions are not altered by estimating the models with the expanded set of regressors. In particular, u^{min} or u^{begin} are not significant once selection is controlled for in accordance with our theory. Allowing for even more regressors (for $m > 2$) renders many of them insignificant but still does not affect any of our conclusions.

As a robustness check of our results, we also conduct the Davidson and MacKinnon (1981) J test to distinguish between the competing models. The idea of the J test is that including the fitted values of the second model into the set of regressors of a correctly specified first model should provide no significant improvement. If instead it does, then the first model is rejected.[18] Table 5 represents the results from comparing our model including the regressors q^{MH} and q^{EH} with the contracting models which imply including u^{min}, including u^{begin} or

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[16]The only difference is that with more curvature in tenure current unemployment has significant impact on wages even after the effect of past labor market conditions is accounted for.

[17]The regressor $\tilde{\sigma}^{max}$ becomes however strongly significant when we do not control for individual fixed effects, echoing the view expressed for example in Solon, Barsky, and Parker (1994), that a substantial composition bias is present: low-skill workers tend to be employed in booms rather than recessions.

[18]To test model $M_1 : y = X\beta + u_1$ against the alternative model $M_2 : y = Z\beta + u_2$, Davidson and MacKinnon

including both u^{min} and u^{begin}. All three model comparisons show that the rigid wage model *is* rejected in favor of our search model and that the search model *cannot* be rejected in favor of a rigid wage model.[19]

A potential concern about these finding is whether they reflect genuine business cycle relationships or are affected by the presence of trends in variables, i.e., a secular rise in wages and a decline in unemployment rates over the sample period. To alleviate this concern we repeated the analysis using de-trended unemployment to construct measures of u, u^{min} and u^{begin}. (We used the HP-filter (Prescott (1986)) with a smoothing parameter of 1600 to de-trend the quarterly unemployment rate data.) The results are reported in Appendix II. None of our substantive conclusions is affected by using the de-trended series. In addition, we repeated the analysis by including a full set of time dummies into the regressions instead of the current unemployment rate. In the second step we regressed the estimated coefficients for time dummies on u and found that u is an important predictor of wages. While the estimated coefficients on u differ somewhat between the two procedures on unfiltered data, they are nearly identical when the estimation is based on de-trended unemployment.

In Table 6 we compare the wage volatility of job stayers and job switchers. Consistent with the existing literature, we find that wages of job switchers are considerably more cyclical. The literature has rationalized this finding as evidence for implicit contracts that shield employed workers from the influence of outside labor market conditions. However, once we control for selection, we find no difference in the cyclical behavior of wages for job stayers and job

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(1981) suggest to test whether $\alpha = 0$ in

$$y = X\beta + \alpha Z\hat{\gamma} + u, \tag{29}$$

where $\hat{\gamma}$ is the vector of OLS estimates of the M_2 model. Rejecting $\alpha = 0$ is then a rejection of M_1. Reversing the roles of M_1 and M_2 allows to test M_2.

[19]As a further robustness check, we also conducted the J_A test proposed by Fisher and McAleer (1981) to distinguish between the competing models. The J_A is similar so the J test as it tests $\alpha = 0$ in

$$y = X\beta + \alpha Z\tilde{\gamma} + u, \tag{30}$$

where $\tilde{\gamma}$ is the result of first regressing y on X and then regressing the fitted value of this regression on Z. Again rejecting $\alpha = 0$ is a rejection of M_1. The results of this test are very similar to the results of the J test (consequently, we do not present a separate Table with these results) and imply that the rigid wage model is rejected in favor of our search model and the search model cannot be rejected in favor of a rigid wage model.

switchers.

Beaudry and DiNardo (1991) show that contracts imply that the current wage depends on initial conditions or on the best business cycle conditions experienced during the current job. Adding u^{min} and u^{begin} to wage regressions is then a test for the importance of contracts. Another test for contracts is to consider how the slope of the tenure profile changes over the business cycle. A model with contracts implies that the cross-sectional tenure profile is steeper in a recession than in a boom. Workers hired in a recession (low tenure workers in a recession) are not shielded from the current adverse business cycle conditions whereas workers hired before the recession started (high tenure workers in a recession) are shielded through contracts agreed upon under better conditions. Workers hired in a boom (low tenure workers in a boom) benefit from the improved business cycle conditions whereas high tenure workers do not benefit as much as their terms were set earlier. As result, the difference between wages of low- and high tenure workers is smaller in a boom than in a recession. This implication is supported by our data as shown the first column of Table 7. The interaction between tenure and unemployment is found to be positive. We then investigate whether this result is again driven by selection effects. We proceed as before and add our regressors. Columns 2 and 3 of Table 7 establish that the interaction between tenure and unemployment becomes insignificant once we control for selection.

A different type of wage rigidity is exhibited by search models that feature commitment of firms to future wages and to matching outside offers (e.g., Cahuc, Postel-Vinay, and Robin (2006)). In these models with search frictions offers arrive only with a certain probability (less than one) and the current firm can counter these offers. A worker who has received more offers has also obtained and accepted more counter offers from the current firm. As a result his wage is likely to be higher than the wage of someone who has received fewer offers. These arguments imply that the number of offers from the beginning of the current job until period t is an important determinant for the wage in period t. This can be implemented by adding $q_t^{Contract} = q_{1+T_{k-1}} + \ldots + q_t$ for $1 + T_{k-1} \leq t \leq T_k$, the expected number of offers between period $1 + T_{k-1}$ and t, to the wage regressions. We find indeed that $q_t^{Contract}$ is a positively significant determinant of wages in a standard wage regression. We then again ask whether this finding is driven by selection effects. To this end, we add our regressors to the previous regression.

Table 8 shows that q^{HM} and q^{EH} are significant whereas $q_t^{Contract}$ becomes insignificant. We conclude that selection effects are the primary determinant of wages. The main difference between adding $q_t^{Contract}$ and adding q^{HM} is that q^{HM} incorporates information from the full job spell whereas $q_t^{Contract}$ incorporates only information until period t. The contracting model implies that the period t wage increases with the number of offers until period t. Our model instead implies that the match quality is constant during every job and that all the information available from the current job spell should be used to measure this match quality. The data suggest that the latter possibility is a better description of wage formation.

6   Model Simulation

We showed theoretically in Sections 2 and 3 that our model can qualitatively generate the patterns in the data that have been interpreted as evidence for certain rigidities. The objective of this section is to assess whether our model can also reproduce the magnitudes found in this literature. Since this question is quantitative we parameterize the model to match the U.S. labor market facts.

Since we are only interested in how wages are set given aggregate labor market conditions, the model is partial equilibrium. This means that the stochastic driving force is an exogenous process instead of being the result of a general equilibrium model with optimizing agents.[20] However, since we have to match the model to the data, we have to take a stand on what the driving force is. We choose market tightness, since this variable determines the probability to receive offers, which in turn determines the evolution of unemployment.

We choose the model period to be one month. Since allowing for endogenous separations has very little impact on our main empirical findings, we consider exogenous separations only. The stochastic process for market tightness is assumed to follow an AR(1) process:

$$\log \theta_{t+1} = \rho \log \theta_t + \nu_{t+1}, \tag{31}$$

where $\rho \in (0,1)$ and $\nu \sim N(0, \sigma_\nu^2)$. To calibrate ρ and σ_ϵ^2, we consider quarterly averages of monthly market tightness and HP-filter (Prescott (1986)) this process with a smoothing

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[20]We can thus not answer the question whether this process and the model's endogenous variables could be the mutually consistent outcome of a general equilibrium model. We leave this interesting question for future research.

parameter of 1600, commonly used with quarterly data. In the data we find an autocorrelation of 0.924 and an unconditional standard deviation of 0.206 for the HP-filtered process. However, at monthly frequency, there is no $\rho < 1$ which generates such a high persistence after applying the HP-filter. We therefore choose $\rho = 0.99$, since higher values virtually do not increase the persistence of the HP-filtered process in the simulation. For this persistence parameter we set $\sigma_\nu = 0.095$ in the model to replicate the observed volatility of market tightness. The mean of θ is normalized to one.

An unemployed worker receives up to M offers per period, each with probability λ, and an employed worker receives up to M offers per period, each with probability q. We assume that both λ and q are functions of the driving force θ:

$$\log \lambda_t = \log \overline{\lambda} + \kappa \log \theta_t \qquad \text{and} \tag{32}$$

$$\log q_t = \log \overline{q} + \kappa \log \theta_t. \tag{33}$$

Since an unemployed worker accepts every offer, the probability to leave unemployment within one period equals $1 - (1 - \lambda)^M$ - the probability to receive at least one offer - and the probability to stay unemployed equals $(1 - \lambda)^M$ - the probability of receiving no offers. Thus the unemployment rate evolves according to

$$u_{t+1} = u_t(1 - \lambda)^M + s(1 - u_t). \tag{34}$$

A job-holder receives k offers with probability $\binom{M}{k} q^k (1-q)^{(M-k)}$. However, not every received offer leads to a job-switch, since workers change jobs only if the new job features a higher idiosyncratic productivity level ϵ^i. Thus the probability to switch jobs depends not only on q but also on the distribution of ϵ^i, which endogenously evolves over time.

A new value of ϵ is drawn, according to a distribution function F, which is assumed to be normal, $F = \mathcal{N}(\mu_\epsilon, \sigma_\epsilon^2)$, and truncated at two standard deviations, so that the support equals $[\underline{\epsilon}, \overline{\epsilon}] = [\mu_\epsilon - 2\sigma_\epsilon, \mu_\epsilon + 2\sigma_\epsilon]$. Finally the log wage equals

$$\log w_t^i = \alpha u_t + \beta \log \epsilon_t^i. \tag{35}$$

We normalize $\beta = 1$ since β and σ_ϵ are not jointly identified. The following seven parameters then have to be determined: the average levels of receiving an offer for unemployed and

employed workers $\overline{\lambda}$ and $\overline{q}$, the elasticities of the offer probabilities κ, the mean and the volatility of idiosyncratic productivity μ_ϵ and σ_ϵ^2, the maximum number of offers, M and the coefficient α of the linear wage equation.

As targets we use properties of the probability to find a job, of the probability to switch a job, of wages and of unemployment. Specifically we find that the average monthly job finding rate equals 0.43[21], the average monthly probability to switch jobs equals 0.029 (Nagypal (2008)) and we set $s = 0.028$ to match an unemployment rate of 6.2%.

We also target the following three wage regressions which describe the elasticity of wages w.r.t. unemployment u and minimum unemployment u^{min} (coefficients are multiplied by 100):

$$\log w_t \;=\; -2.828 u_t + \eta_t, \tag{36}$$

$$\log w_t \;=\; -4.000 u_t^{min} + \eta_t, \tag{37}$$

$$\log w_t \;=\; -0.466 u_t - 3.561 u_t^{min} + \eta_t, \tag{38}$$

where η_t is the error term (different in all regressions). We also target the following two wage regressions which describe the elasticity of wages w.r.t. unemployment at the beginning of the job u^{begin} (coefficients are multiplied by 100):

$$\log w_t \;=\; -2.613 u_t^{begin} + \eta_t, \tag{39}$$

$$\log w_t \;=\; -2.037 u_t - 1.472 u_t^{begin} + \eta_t. \tag{40}$$

Furthermore we target the elasticity of job-stayers $\beta^{Stay} = -2.233$ and of job switchers $\beta^{Switch} = -3.505$ and the wage gains of job-to-job switchers $wg^{EE} = 0.1$ and of workers hired after a spell of unemployment $wg^{UE} = -0.07$. Finally we consider quarterly averages of monthly unemployment and HP-filter this process with a smoothing parameter of 1600. We find a standard deviation of 0.090 and use this number as an additional target.

To obtain the corresponding estimate in the model, we first replicate the sampling of the data. We then estimate regressions on our model-generated data identical to the ones estimated on the NLSY data. The resulting regression coefficients are our calibration targets.

Note that since the wages of stayers change only due to changes in aggregate unemployment, the elasticity β^S identifies α, the coefficient of unemployment in the wage equation, so

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[21]This number was computed from data constructed by Robert Shimer. For additional details, please see Shimer (2007) and his webpage http://robert.shimer.googlepages.com/flows.

that $\alpha = \beta^S = -2.233$.

The computation of the model is simple. We just simulate the model to generate artificial time series for tightness, unemployment and wages. To do so, we start with an initial value for unemployment and tightness and draw a new tightness shock according to the AR(1) process described above. Knowing θ allows us to compute the probabilities to receive an offer both for unemployed and employed workers and thus we can compute the evolution of the unemployment rate and finally wages. Iterating this procedure generates the time series of interest.

The performance of the model in matching calibration targets is described in Table 9 and the calibrated parameter values can be found in Table 10. Our parsimoniously parameterized model can hit the targets quite well. This is remarkable as we effectively have only six parameters, $\overline{\lambda}$, $\overline{q}$, κ, μ_ϵ, σ_ϵ^2 and M, to match thirteen targets. The model can replicate the magnitudes we observe in the data. The wages of both job-to-job switchers and stayers are substantially more volatile than the wages of stayers, as our theory predicts. We also find a large coefficient for u^{min}, suggesting that it is an important determinant of wages.

We then add our regressors q^{MH} and q^{EH} to these regressions in the same way we did in the data. The results from these regressions are presented in Tables 11 and 12 and confirm our theoretical findings. Once we control for match specific idiosyncratic productivity, the evidence for the kind of rigidity of wages we consider in this paper disappears.

Finally, we can compute the amount of wage inequality generated by the model. Since wage inequality arises in this model only because of frictions, measuring inequality allows us to assess the amount of frictions that is needed to match our targets, including the coefficients on the "rigidity vriables". We find that the cross-sectional variance of log wages in the calibrated model equals 0.009. This is a small number relative to the observed within group variance of log wages in the US data of about 0.25 (Kambourov and Manovskii (2009)). Since we generate less than 5% of observed wage-inequality, we conclude that only a small amount of frictions is needed to replicate the empirical findings. Interestingly, we also find that the variance of wages generated by frictions is very similar in the model and in the data. To compute the variance in the data we use the variation in wages accounted for by q^{MH} and q^{EH} from a wage regression that includes these two regressors, the current unemployment rate and all other

controls such as tenure and experience. We find that q^{MH} and q^{EH} explain a cross-sectional variance of log wages of 0.009, the same number we compute in the model. We could have imposed the variance of wages as an additional target to discipline the amount of frictions in our model. Our results show that this is not necessary. The amount of frictions needed to rationalize the importance of the 'rigidity variables' is the same that we find independently in the data.

7   Conclusion

We consider a model with on-the-job search where current wages are spot, i.e., they depend only on current aggregate labor market conditions and idiosyncratic productivities. We nevertheless find that our model generates many features that have been interpreted as evidence against a spot market model. Past aggregate labor market conditions, e.g., the lowest unemployment rate during a job spell, have explanatory power for current wages. Such a history dependence arises because the expected wage depends on the number of offers received since the job started. Since more offers arrive in a boom than in recession, the expected number of offers and thus wages are higher if the worker has experienced better times. The same mechanism explains why the business cycle conditions at the start of an employment spell affect wages in later periods. A worker hired in a recession has received fewer offers than a worker hired in a boom and thus has to accept a lower starting wage which will only gradually catch up. Higher cyclical wage volatility of job switchers is also consistent with the model with on-the-job search because workers sample from a larger pool of offers in a boom than in a recession, and workers with a lower match quality benefit more from the expansion of the pool of offers in a boom.

We provide direct tests of this evidence for rigidities against a spot wage model with on-the-job search and find that this evidence is rejected in favor of the spot wage model. Once we measure the expected number of offers and include them in regressions to control for unobserved idiosyncratic productivity, the lowest unemployment rate during a job spell and the unemployment rate at the beginning of the employment spell become insignificant. Furthermore the differences in the volatility of wages between job switchers and job stayers

disappears.

The key innovation in the paper is the proposed method for identifying the quality of job matches in the data. We show that the expected job match quality can be approximated by the expected number of offers. We then demonstrate that the expected number of offers can be measured by the sum of market tightness during the same period. We use this method to establish our results in this paper but we expect that it will also be valuable to address other questions. For example, the literature which aims to measure the returns to tenure and experience (Altonji and Shakotko (1987), Topel (1991)) suffers from an identification problem due to the non-observability of match specific productivity. Once one is able to control for match specific productivity, as we suggest that our method can, these problems disappear and the returns to tenure and experience can be estimated in an unbiased way.

Finally, we view our empirical results as providing some restrictions and guidance to the development of labor market models. We think that a successful model should be consistent with the empirical regularities that we discover in this paper. In particular, the model-generated data should replicate the importance of our regressors and the insignificance of the "rigidity variables" in their presence. In this paper we proposed a simple model which satisfies these requirements. While we believe that this simple model is an important building block of a more complete and empirically successful model of the labor market, we of course cannot rule out the presence of more elaborated wage setting mechanisms.[22] But our results will hopefully prove useful in distinguishing between various competing theories.

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[22]For example, our results are silent on insurance contracts against idiosyncratic risk and are consistent with results for example of Guiso, Pistaferri, and Schivardi (2005) who find that firms fully absorb temporary idiosyncratic fluctuations.

Table 1: Rigid Wages or On-the-Job Search? NLSY Data.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-2.828**	**-1.150**	-0.466	**-0.954**	**-2.038**	**-1.221**
		(0.278)	(0.275)	(0.411)	(0.407)	(0.328)	(0.317)
2.	u^{min}	—	—	**-3.561**	-0.312	—	—
		—	—	(0.546)	(0.566)	—	—
3.	u^{begin}	—	—	—	—	**-1.472**	0.145
		—	—	—	—	(0.394)	(0.412)
4.	q^{HM}	—	**6.169**	—	**6.135**	—	**6.179**
		—	(0.361)	—	(0.370)	—	(0.365)
5.	q^{EH}	—	**3.129**	—	**3.095**	—	**3.163**
		—	(0.403)	—	(0.412)	—	(0.425)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 2: Rigid Wages or On-the-Job Search? NLSY Data.
Specification with Tenure and Experience Dummies.

Variable	Specification					
	1	2	3	4	5	6
1. u	**-3.109**	**-1.336**	**-1.009**	**-1.187**	**-2.347**	**-1.350**
	(0.297)	(0.297)	(0.449)	(0.444)	(0.351)	(0.342)
2. u^{min}	—	—	**-3.125**	-0.236	—	—
	—	—	(0.574)	(0.590)	—	—
3. u^{begin}	—	—	—	—	**-1.413**	0.028
	—	—	—	—	(0.400)	(0.417)
4. q^{HM}	—	**5.837**	—	**5.815**	—	**5.839**
	—	(0.375)	—	(0.382)	—	(0.377)
5. q^{EH}	—	**3.087**	—	**3.063**	—	**3.094**
	—	(0.397)	—	(0.405)	—	(0.419)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 3: Rigid Wages or On-the-Job Search? NLSY Data. Specification with Endogenous Separations.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-2.828**	**-0.990**	-0.466	**-1.004**	**-2.038**	**-1.205**
		(0.278)	(0.279)	(0.411)	(0.414)	(0.328)	(0.321)
2.	u^{min}	—	—	**-3.561**	0.024	—	—
		—	—	(0.546)	(0.603)	—	—
3.	u^{begin}	—	—	—	—	**-1.472**	0.522
		—	—	—	—	(0.394)	(0.474)
4.	q^{HM}	—	**6.216**	—	**6.219**	—	**6.256**
		—	(0.363)	—	(0.376)	—	(0.370)
5.	q^{EH}	—	**4.180**	—	**4.189**	—	**4.589**
		—	(0.681)	—	(0.738)	—	(0.818)
6.	$\tilde{\sigma}^{max}$	—	0.210	—	0.206	—	0.015
		—	(0.498)	—	(0.513)	—	(0.535)
7.	Σ^{max}	—	**1.200**	—	**1.199**	—	**1.307**
		—	(0.448)	—	(0.454)	—	(0.462)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 4: Rigid Wages or On-the-Job Search? NLSY Data. Recursive Specifications with Endogenous Separations.

	Variable	Specification					
		One Lag			Two Lags		
		1	2	3	4	5	6
1.	u	**-1.136**	**-1.071**	**-1.193**	**-1.212**	**-1.052**	**-1.209**
		(0.237)	(0.366)	(0.269)	(0.243)	(0.366)	(0.270)
2.	u^{min}	—	-0.110	—	—	-0.284	—
		—	(0.471)	—	—	(0.486)	—
3.	u^{begin}	—	—	0.135	—	—	-0.009
		—	—	(0.307)	—	—	(0.322)
4.	q^{HM}	**6.030**	**6.018**	**6.040**	**6.057**	**6.027**	**6.057**
		(0.260)	(0.265)	(0.261)	(0.261)	(0.266)	(0.261)
5.	q^{HM}_{-1}	**1.423**	**1.421**	**1.434**	**1.458**	**1.439**	**1.457**
		(0.272)	(0.272)	(0.273)	(0.261)	(0.278)	(0.281)
6.	q^{HM}_{-2}	—	—	—	**1.176**	**1.199**	**1.178**
		—	—	—	(0.393)	(0.395)	(0.396)
7.	q^{EH}_{-1}	**3.226**	**3.180**	**3.334**	—	—	—
		(0.540)	(0.575)	(0.597)	—	—	—
8.	q^{EH}_{-2}	—	—	—	**2.620**	**2.448**	**2.610**
		—	—	—	(0.647)	(0.711)	(0.749)
9.	$\tilde{\sigma}^{max}$	0.275	0.284	0.248	0.315	-0.284	0.317
		(0.343)	(0.345)	(0.349)	(0.347)	(0.486)	(0.322)
10.	$\tilde{\sigma}^{max}_{-1}$	**1.515**	**1.517**	**1.513**	**1.680**	**1.653**	**1.678**
		(0.444)	(0.444)	(0.444)	(0.463)	(0.464)	(0.468)
11.	$\tilde{\sigma}^{max}_{-2}$	—	—	—	**1.972**	**2.006**	**1.974**
		—	—	—	(0.650)	(0.652)	(0.654)
12.	Σ^{max}_{-1}	**1.740**	**1.716**	**1.800**	—	—	—
		(0.487)	(0.498)	(0.505)	—	—	—
13.	Σ^{max}_{-2}	—	—	—	**2.606**	**2.926**	**3.004**
		—	—	—	(0.604)	(0.704)	(0.713)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 5: J Test: Search Model vs. Rigid Wage Models. NLSY Data.

Tested Model	Alternative Model			
	q^{MH}, q^{EH}	u^{min}	u^{begin}	u^{min}, u^{begin}
q^{MH}, q^{EH}	—	0.26	-0.41	0.38
u^{min}	**27.16**	—-	—	—
u^{begin}	**27.72**	—-	—	—
u^{min}, u^{begin}	**27.16**	—-	—	—

Note - Entries are t-statistic from testing the variable in the first column against the the alternative in the first row. A bold value denotes significance at the 5% level: the tested model is rejected in favor of the alternative model.

Table 6: Wage Volatility of Job Stayers and Switchers. NLSY Data.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-2.234**	**-3.505**	**-1.872**
		(0.372)	(0.487)	(0.4497)
2.	q^{HM}	—	—	**5.402**
		—	—	(0.402)
3.	q^{EH}	—	—	**3.767**
		—	—	(0.701)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.

Table 7: Changing Tenure Profiles.

	Variable	Specification		
		1	2	3
1.	u	**-3.212**	**-1.088**	**-0.955**
		(0.323)	(0.324)	(0.346)
2.	$tenure * u$	**0.004**	0.001	0.001
		(0.001)	(0.001)	(0.001)
3.	q^{HM}	—	**6.181**	**6.237**
		—	(0.363)	(0.366)
4.	q^{EH}	—	**3.135**	**4.222**
		—	(0.405)	(0.693)
5.	$\tilde{\sigma}^{max}$	—	—	0.195
		—	—	(0.500)
6.	Σ^{max}	—	—	**1.213**
		—	—	(0.450)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 8: Contracts or On-the-Job Search? NLSY Data.

	Variable	Specification		
		1	2	3
1.	u	**-1.555**	**-1.209**	**-1.059**
		(0.278)	(0.277)	(0.282)
2.	$q^{Contract}$	**5.199**	-0.345	-0.434
		(0.474)	(0.547)	(0.542)
3.	q^{HM}	—	**6.296**	**6.375**
		—	(0.421)	(0.424)
4.	q^{EH}	—	**3.136**	**4.216**
		—	(0.404)	(0.681)
5.	$\tilde{\sigma}^{max}$	—	—	0.193
		—	—	(0.496)
6.	Σ^{max}	—	—	**1.208**
		—	—	(0.449)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 9: Matching the Calibration Targets.

	Target	Value	
		Data	Model
1.	Semi-Elasticity of wages wrt agg. unemployment u	-2.828	-3.077
2.	Semi-Elasticity of wages wrt minimum unemployment u_{min}	-4.000	-4.039
3.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{min})	-0.466	-0.599
4.	Semi-Elasticity of wages wrt minimum unemployment u^{min} (joint reg. with u)	-3.561	-3.477
5.	Semi-Elasticity of wages wrt starting unemployment u^{begin}	-2.613	-2.656
6.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{begin})	-2.037	-2.421
7.	Semi-Elasticity of wages wrt starting unemployment u^{begin} (joint reg. with u)	-1.472	-0.969
8.	Semi-Elasticity of wages wrt unemployment for stayers, β^{Stay}	-2.233	-2.233
9.	Semi-Elasticity of wages wrt unemployment for switchers, β^{Switch}	-3.505	-3.269
10.	Wage-Gains for job-to-job switchers, wg^{EE}	0.100	0.097
11.	Wage-Gains after unemployment spell, wg^{UE}	-0.070	-0.082
12.	Monthly job-finding rate for unemployed	0.430	0.490
13.	Monthly job-to-job probability for employed	0.029	0.024
14.	Std. of aggregate unemployment	0.090	0.102

Note - The table describes the performance of the model in matching the calibration targets.

Table 10: Calibrated Parameter Values.

Parameter	Definition	Value
α	coefficient on unemployment in wage equation	-2.233
β	coefficient on ϵ in wage equation	1.000
$\overline{\lambda}$	avg. prob to receive an offer for unemployed	0.112
$\overline{q}$	avg. prob to receive an offer for employed	0.017
κ	elasticity of the offer probability	0.744
M	max number of offers per period	6
μ_ϵ	mean of idiosyncratic productivity	0.435
σ_ϵ	std. of idiosyncratic productivity	0.054
ρ	persistence of aggregate process	0.990
σ_ν	std. of aggregate process	0.095

Note - The table contains the calibrated parameter values in the benchmark calibration.

Table 11: Rigid Wages or On-the-Job Search? Model.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	-3.077	-1.879	-0.599	-1.813	-2.421	-1.903
2.	u^{min}	—	—	-3.477	-0.104	—	—
3.	u^{begin}	—	—	—	—	-0.969	0.037
4.	q^{HM}	—	4.140	—	4.101	—	4.145
5.	q^{EH}	—	1.940	—	1.936	—	1.943

Note - All coefficients are multiplied by 100.

Table 12: Wage Volatility of Job Stayers and Switchers. Model.

	Variable	Job Stayers	Job Switchers	
		1	2	3
1.	u	-2.233	-3.269	-2.052
2.	q^{HM}	—	—	2.734
3.	q^{EH}	—	—	3.778

Note - All coefficients are multiplied by 100.

References

ABRAHAM, K. G., AND H. FARBER (1987): "Job Duration, Seniority and Earnings," *American Economic Review*, 77(3), 278–97.

AIYAGARI, R. S., L. J. CHRISTIANO, AND M. EICHENBAUM (1992): "The Output, Employment, and Interest Rate Effects of Government Consumption," *Journal of Monetary Economics*, 30(1), 73–86.

ALTONJI, J., AND R. SHAKOTKO (1987): "Do Wages Rise with Job Seniority," *Review of Economic Studies*, 54, 437–459.

BARLEVY, G. (2002): "The Sullying Effect of Recessions," *Review of Economic Studies*, 69(1), 65–96.

——— (2008): "Identification of Search Models using Record Statistics," *Review of Economic Studies*, 75(1), 29–64.

BEAUDRY, P., AND J. DINARDO (1991): "The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from Micro Data," *Journal of Political Economy*, 99(4), 665–688.

BILS, M. J. (1985): "Real Wages over the Business Cycle: Evidence from Panel Data," *Journal of Political Economy*, 93(4), 666–689.

BOLDRIN, M., AND M. HORVATH (1995): "Labor Contracts and Business Cycles," *Journal of Political Economy*, 103(5), 972–1004.

BOWLUS, A. J., AND H. LIU (2007): "The Long-term Effects of Graduating from High School During a Recession: Bad Luck or Forced Opportunity?," mimeo, Univ. of Western Ontario.

BURDETT, K. (1996): "Truncated Means and Variances," *Economic Letters*, 52(3), 263–267.

CAHUC, P., F. POSTEL-VINAY, AND J.-M. ROBIN (2006): "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, 74(2), 323–364.

DAVIDSON, R., AND J. G. MACKINNON (1981): "Several Tests for Model Specification in the Presence of Alternative Hypotheses," *Econometrica*, 49, 781793.

ECKSTEIN, Z., AND K. WOLPIN (1989): "Dynamic Labour Force Participation of Married Women and Endogenous Work Experience," *Review of Economic Studies*, 56(3), 375–390.

FISHER, G. R., AND M. MCALEER (1981): "Alternative Procedures and Associated Tests of Significance for Non-nested Hypotheses," *Journal of Econometrics*, 16, 103–119.

GERTLER, M., AND A. TRIGARI (2009): "Unemployment Fluctuations with Staggered Nash Bargaining," *Journal of Political Economy*, 117(1), 38–86.

GOMES, J., J. GREENWOOD, AND S. REBELO (2001): "Equilibrium Unemployment," *Journal of Monetary Economics*, 48(1), 109–152.

GOMME, P., AND J. GREENWOOD (1995): "On the Cyclical Allocation of Risk," *Journal of Economic Dynamics and Control*, 19, 91–124.

GREENE, W. H. (2002): *Econometric Analysis.* New York, NY: Prentice Hall.

GUISO, L., L. PISTAFERRI, AND F. SCHIVARDI (2005): "Insurance within the Firm," *Journal of Political Economy*, 113, 1054–1087.

HAGEDORN, M., AND I. MANOVSKII (2008): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 98(4), 1692–1706.

KAHN, L. (2007): "The Long-Term Labor Market Consequences of Graduating College in a Bad Economy," mimeo, Yale School of Management.

KAMBOUROV, G., AND I. MANOVSKII (2009): "Occupational Mobility and Wage Inequality," *Review of Economic Studies*, 76(2), 731–759.

KREBS, T. (2007): "Job Displacement Risk and the Cost of Business Cycles," *American Economic Review*, 97(3), 664–686.

KYDLAND, F. E., AND E. C. PRESCOTT (1982): "Time to Build and Aggregate Fluctuations," *Econometrica*, 50, 1345–1370.

LONG, J. B. J., AND C. I. PLOSSER (1983): "Real Business Cycles," *Journal of Political Economy*, 91(1), 36–69.

LUCAS, R. J. (1987): "Models of Business Cycles," in *Yrjo Jahnsson Lectures.* Blackwell Publishing.

———— (2003): "Macroeconomic Priorities," *American Economic Review*, 93(1), 1–14.

MCDONALD, J. T., AND C. WORSWICK (1999): "Wages, Implicit Contracts, and the Business Cycle: Evidence from Canadian Micro Data," *Journal of Political Economy*, 107(4), 884–892.

MORTENSEN, D., AND C. PISSARIDES (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61(3), 397–415.

NAGYPAL, E. (2008): "Worker Reallocation over the Business Cycle: The Importance of Employer-to-Employer Transitions," mimeo, Northwestern University.

OREOPOULOS, P., T. VON WACHTER, AND A. HEISZ (2008): "Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates," mimeo, Columbia University.

PISSARIDES, C. (2008): "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?," *Econometrica, Forthcoming.*

POSTEL-VINAY, F., AND J.-M. ROBIN (2002): "Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 70(6), 2295–2350.

PRESCOTT, E. (1986): "Theory Ahead of Business Cycle Measurement," *Federal Reserve Bank of Minneapolis Quarterly Review*, 10, 9–22.

SHIMER, R. (2007): "Reassesing the Ins and Outs of Unemployment," mimeo, University of Chicago.

SOLON, G., R. BARSKY, AND J. A. PARKER (1994): "Measuring the Cyclicality of Real Wages: How Important Is Composition Bias," *Quarterly Journal of Economics*, 109(1), 1–25.

TOPEL, R. H. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99(1), 145–76.

WOLPIN, K. I. (1992): "The Determinants of Black-White Differences in Early Employment Careers: Search, Layoffs, Quits, and Endogenous Wage Growth," *Journal of Political Economy*, 100(3), 535–560.

I Proofs and Derivations

I.1 Deriving $\tilde{F}^k(\epsilon|N_t^k)$

We consider a worker who not only received an offer in period $1 + T_{k-1}$ but also accepted this offer. Let G be the probability that this switcher accepts an offer less than $\hat{\epsilon}$. The information that the worker switches makes it necessary to modify the probability, $F(\hat{\epsilon})$, which describes the unconditional probability to accept an offer. For a switcher the probability is zero if $\hat{\epsilon} \leq \epsilon_{k-1}$, what is equivalent to $\epsilon_k \geq \epsilon_{k-1}$. As it still holds that $G(\bar{\epsilon}) = 1$, it follows that

$$G(\hat{\epsilon}) = \frac{F(\hat{\epsilon}) - F(\epsilon_{k-1})}{1 - F(\epsilon_{k-1})} \tag{A1}$$

for $\hat{\epsilon} \geq \epsilon_{k-1}$. To derive the probability for later periods, consider a worker of type ϵ, who has received N_t^k offers. This worker declines all offers less than ϵ what happens with probability $F(\epsilon)^{N_t^k}$. Thus the probability that the worker has a type less than $\hat{\epsilon}$ equals[23]

$$\frac{(1 - F(\epsilon_{k-1}))(1 + N_t^k)}{1 - F(\epsilon_{k-1})^{1+N_t^k}} \int_{\epsilon_{k-1}}^{\hat{\epsilon}} F(\epsilon)^{N_t^k} dG(\epsilon) = \frac{F(\hat{\epsilon})^{1+N_t^k} - F(\epsilon_{k-1})^{1+N_t^k}}{1 - F(\epsilon_{k-1})^{1+N_t^k}}. \tag{A2}$$

I.2 Determining Signs of c_1 and c_2

We first show that for $\tilde{N} > N$ and $\epsilon_{k-1} \leq \hat{\epsilon} \leq \bar{\epsilon}$

$$\Delta_{\tilde{N},N}(\hat{\epsilon}) = \Omega_{\tilde{N}}(\hat{\epsilon}) - \Omega_N(\hat{\epsilon}) \leq 0, \tag{A3}$$

where

$$\Omega_N(\hat{\epsilon}) = \frac{F(\hat{\epsilon})^N - F(\epsilon_{k-1})^N}{1 - F(\epsilon_{k-1})^N} \tag{A4}$$

$$\Omega_{\tilde{N}}(\hat{\epsilon}) = \frac{F(\hat{\epsilon})^{\tilde{N}} - F(\epsilon_{k-1})^{\tilde{N}}}{1 - F(\epsilon_{k-1})^{\tilde{N}}}. \tag{A5}$$

$$\Delta_{\tilde{N},N}(\hat{\epsilon}) = \int_{\epsilon_{k-1}}^{\hat{\epsilon}} \left\{ \frac{\tilde{N}F(\epsilon)^{\tilde{N}-1}}{1 - F(\epsilon_{k-1})^{\tilde{N}}} - \frac{NF(\epsilon)^{N-1}}{1 - F(\epsilon_{k-1})^N} \right\} f(\epsilon) d\epsilon \tag{A6}$$

$$= \int_{\epsilon_{k-1}}^{\hat{\epsilon}} \frac{NF(\epsilon)^{N-1}f(\epsilon)}{1 - F(\epsilon_{k-1})^N} (\omega F(\epsilon)^{\tilde{N}-N} - 1) d\epsilon, \tag{A7}$$

---

[23]Since $m := \int_{\epsilon_{k-1}}^{\bar{\epsilon}} F(\epsilon)^{N_t^k} dG(\epsilon) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} F(\epsilon)^{N_t^k} \frac{f(\epsilon)}{1-F(\epsilon_{k-1})} d\epsilon = \frac{F(\bar{\epsilon})^{1+N_t^k} - F(\epsilon_{k-1})^{1+N_t^k}}{(1+N_t^k)(1-F(\epsilon_{k-1}))} = \frac{1 - F(\epsilon_{k-1})^{1+N_t^k}}{(1+N_t^k)(1-F(\epsilon_{k-1}))}$, we have to adjust by the factor $1/m$ to define a probability measure.

where

$$\omega = \frac{\tilde{N}(1 - F(\epsilon_{k-1})^N)}{N(1 - F(\epsilon_{k-1})^{\tilde{N}})}. \tag{A8}$$

Since both Ω_N and $\Omega_{\tilde{N}}$ are probability measures on $[\epsilon_{k-1}, \bar{\epsilon}]$ it holds that

$$\Delta_{\tilde{N},N}(\bar{\epsilon}) = 0. \tag{A9}$$

Since $\Delta_{\tilde{N},N}(\epsilon_{k-1}) = 0$ and $\omega F(\epsilon) - 1$ is increasing in ϵ it follows that an $\tilde{\epsilon}$ exists such that $\omega F(\tilde{\epsilon}) - 1 = 0$, $\omega F(\epsilon) - 1 < 0$ for $\epsilon < \tilde{\epsilon}$ and $\omega F(\epsilon) - 1 > 0$ for $\epsilon < \tilde{\epsilon}$. This implies that $\Delta_{\tilde{N},N}(\hat{\epsilon}) \leq 0$ for all $\epsilon_{k-1} \leq \hat{\epsilon} \leq \bar{\epsilon}$.[24]

We can now turn to the linearization of

$$E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) = \bar{\epsilon} - \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \frac{F(\epsilon)^{1+N^k_{T_k}} - F(\epsilon_{k-1})^{1+N^k_{T_k}}}{1 - F(\epsilon_{k-1})^{1+N^k_{T_k}}} d\epsilon \tag{A10}$$

w.r.t. $N^k_{T_k}$ and ϵ_{k-1}. We linearize around a steady state where all variables are evaluated at their expected values in a steady state.

Since we have established that $\Delta_{\tilde{N},N}(\hat{\epsilon}) \leq 0$, the expected value of ϵ_k is increasing in $N^k_{T_k}$. The derivative of $E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k})$ w.r.t. ϵ_{k-1} equals

$$\int_{\hat{\epsilon}}^{\bar{\epsilon}} \frac{(1 - F(\epsilon)^{1+\overline{N}})^2}{(1 - F(\hat{\epsilon})^{1+\overline{N}})^2} (1 + \overline{N}) F(\hat{\epsilon})^{\overline{N}} f(\hat{\epsilon}) d\epsilon > 0, \tag{A11}$$

where $\hat{\epsilon}$ is the steady state value of ϵ_{k-1} and $\overline{N}$ is the steady state value of $N^k_{T_k}$.

I.3 Theory with Endogenous Separations

We now show how the results of the main text have to be modified if workers get separated endogenously. In particular we show that equation (18) approximates ϵ in this case.

The first modification is necessary for $E_t(\epsilon_k|\epsilon_{k-1}, N^k_t)$, which equals

$$E_t(\epsilon_k|\epsilon_{k-1}, N^k_t) = \int_{\tilde{\epsilon}^k_t}^{\bar{\epsilon}} \epsilon d\tilde{F}^k(\epsilon|N^k_t). \tag{A12}$$

We now truncate at $\tilde{\epsilon}^k_t := \max\{\epsilon_{k-1}, \sigma_{1+T_{k-1}}, \ldots, \sigma_t\}$. A worker separates if his type is lower than σ, so that a worker who has survived until period t must have a type larger or equal than $\sigma^k_t = \max\{\sigma_{1+T_{k-1}}, \ldots, \sigma_t\}$.

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[24]Since $\omega F(\epsilon) - 1 < 0$ for $\epsilon < \tilde{\epsilon}$ this is obvious for $\epsilon \leq \tilde{\epsilon}$. Suppose now that $\Delta_{\tilde{N},N}(\hat{\epsilon}) > 0$ for $\hat{\epsilon} > \tilde{\epsilon}$. Since $\omega F(\epsilon) - 1 > 0$ for $\epsilon \geq \hat{\epsilon} \geq \tilde{\epsilon}$ this would imply that $\Delta_{\tilde{N},N}(\bar{\epsilon}) > 0$, contradicting $\Delta_{\tilde{N},N}(\bar{\epsilon}) = 0$.

This truncation makes it also necessary to change the distribution $\tilde{F}^k(\epsilon|N_t^k)$. The probability G that a switcher accepts an offer less than $\hat{\epsilon}$ now equals

$$G(\hat{\epsilon}) = \frac{F(\hat{\epsilon}) - F(\tilde{\epsilon}_{1+T_{k-1}}^k)}{1 - F(\tilde{\epsilon}_{1+T_{k-1}}^k)} \tag{A13}$$

for $\hat{\epsilon} \geq \tilde{\epsilon}_{1+T_{k-1}}^k$. The only difference, due to endogenous separations, is that we replace ϵ_{k-1} by $\tilde{\epsilon}_{1+T_{k-1}}^k$. To derive the probability for later periods, consider again a worker of type ϵ, who has received N_t^k offers. The probability that the worker has a type less than $\hat{\epsilon}$, taking into account endogenous separations, equals[25]

$$\frac{(1 - F(\tilde{\epsilon}_{1+T_{k-1}}^k))(1 + N_t^k)}{1 - F(\tilde{\epsilon}_t^k)^{1+N_t^k}} \int_{\tilde{\epsilon}_t^k}^{\hat{\epsilon}} F(\epsilon)^{N_t^k} dG(\epsilon) = \frac{F(\hat{\epsilon})^{1+N_t^k} - F(\tilde{\epsilon}_t^k)^{1+N_t^k}}{1 - F(\tilde{\epsilon}_t^k)^{1+N_t^k}}, \tag{A14}$$

where the only difference, due to endogenous separations, is that we replace ϵ_{k-1} by $\tilde{\epsilon}_t^k$. We again use the predictor which contains the most information about this ϵ, the value at T_k. The expectation of ϵ_k at $1 + T_{k-1} \leq t \leq T_k$ then equals

$$E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) = \int_{\tilde{\epsilon}_{T_k}^k}^{\bar{\epsilon}} \epsilon d\tilde{F}^k(\epsilon|N_{T_k}^k). \tag{A15}$$

The expression for the expectation of ϵ_k conditional on ϵ_{k-1} stays the same (the modifications are of course incorporated in $E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k)$):

$$E_t(\epsilon_k|\epsilon_{k-1}) = \sum_{N_{T_k}^k} E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) P_{T_k}^k(N_{T_k}^k). \tag{A16}$$

I.3.1 Linearization

Linearization of (A16) w.r.t. $N_{T_k}^k$ and $\tilde{\epsilon}_{T_k}^k$ around a steady state where all variables are evaluated at their expected values in a steady state yields

$$E_t(\epsilon_k|\epsilon_{k-1}, N_{T_k}^k) \approx c_0 + c_1 N_{T_k}^k + c_2 \tilde{\epsilon}_{T_k}^k, \tag{A17}$$

where the coefficients c_1 and c_2 are the first derivatives. The proof in appendix I.2, if ϵ_{k-1} is replaced by $\tilde{\epsilon}_{T_k}^k$, again shows that these coefficients are positive.

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[25]Since $m := \int_{\tilde{\epsilon}_t^k}^{\bar{\epsilon}} F(\epsilon)^{N_t^k} dG(\epsilon) = \int_{\tilde{\epsilon}_t^k}^{\bar{\epsilon}} F(\epsilon)^{N_t^k} \frac{f(\epsilon)}{1 - F(\tilde{\epsilon}_{1+T_{k-1}}^k)} d\epsilon = \frac{F(\bar{\epsilon})^{1+N_t^k} - F(\tilde{\epsilon}_t^k)^{1+N_t^k}}{(1+N_t^k)(1 - F(\tilde{\epsilon}_{1+T_{k-1}}^k))} = \frac{1 - F(\tilde{\epsilon}_t^k)^{1+N_t^k}}{(1+N_t^k)(1 - F(\tilde{\epsilon}_{1+T_{k-1}}^k))}$, we have to adjust by the factor $1/m$ to define a probability measure.

The same arguments as in the main text for the unconditional expectation establish

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2 E_{T_{k-1}}(\tilde{\epsilon}_{T_k}^k). \tag{A18}$$

The difference between this equation and the corresponding one without endogenous separations is that $\tilde{\epsilon}_{T_k}^k$ replaces ϵ_{k-1} (and of course the coefficients may be different).

To simplify $E_{T_{k-1}}(\tilde{\epsilon}_{T_k}^k)$ we use that

$$
\begin{aligned}
E_{T_{k-1}}(\tilde{\epsilon}_{T_k}^k) &= Prob_{T_{k-1}}(\epsilon_{k-1} \geq \sigma_{T_k}^k) E_{T_{k-1}}(\epsilon_{k-1}|\epsilon_{k-1} \geq \sigma_{T_k}^k) + Prob_{T_{k-1}}(\epsilon_{k-1} < \sigma_{T_k}^k)\sigma_{T_k}^k \\
&= E_{T_{k-1}}(\epsilon_{k-1}) + Prob_{T_{k-1}}(\epsilon_{k-1} < \sigma_{T_k}^k)(\sigma_{T_k}^k - E_{T_{k-1}}(\epsilon_{k-1}|\epsilon_{k-1} < \sigma_{T_k}^k)). \tag{A19}
\end{aligned}
$$

We now use the fact that endogenous separations are a binding constraint in the current spell only if $\sigma_{T_k}^k > \Sigma_{k-1}^{max}$, where $\Sigma_{k-1}^{max} = \max\{\sigma_0, \ldots, \sigma_{T_{k-1}}\}$ is the highest value of σ before the current job started. Workers with type $\epsilon < \sigma_k^{max} = \sigma_{T_k}^k$ would be separated but if $\Sigma_{k-1}^{max} > \sigma_k^{max}$ they were already separated before the current spell started. We thus know that $Prob_{T_{k-1}}(\epsilon_{k-1} < \sigma_k^{max}) = 0$ if $\sigma_k^{max} < \Sigma_{k-1}^{max}$ and is positive otherwise (if $\sigma_k^{max} < \bar{\epsilon}$). We therefore approximate the probability by an indicator $\mathcal{I}$ which equals one if $\sigma_k^{max} > \Sigma_{k-1}^{max}$ and equals zero if $\sigma_k^{max} < \Sigma_{k-1}^{max}$. Finally we expect that $(\sigma_k^{max} - E_{T_{k-1}}(\epsilon_{k-1}|\epsilon_{k-1} < \sigma_k^{max}))$ is increasing in σ_k^{max} (Burdett (1996)), so that we get the following approximation:

$$c_2 E_{T_{k-1}}(\tilde{\epsilon}_{T_k}^k) \approx c_2 E_{T_{k-1}}(\epsilon_{k-1}) + c_3 \mathcal{I}_{\sigma_k^{max} > \Sigma_{k-1}^{max}} \sigma_k^{max}, \tag{A20}$$

where we expect c_3 to be positive (but do not impose this restriction). Using these derivations in (A18) yields

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2 E_{T_{k-1}}(\epsilon_{k-1}) + c_3 \tilde{\sigma}_k^{max}, \tag{A21}$$

where $\tilde{\sigma}_k^{max} = \mathcal{I}_{\sigma_k^{max} > \Sigma_{k-1}^{max}} \sigma_k^{max}$.

Again we relate $E_t(\epsilon_k)$ to the worker's employment history before the current job started and apply the derivation for ϵ_k to ϵ_{k-1}. This yields the expected value of $E_t(\epsilon_{k-1})$, for $1 + T_{k-2} \leq t \leq T_{k-1}$:

$$E_t(\epsilon_{k-1}) \approx c_0 + c_1 q_{T_{k-1}}^{HM} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) + c_3 \tilde{\sigma}_{k-1}^{max} \tag{A22}$$

so that for $1 + T_{k-1} \leq t \leq T_k$

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_3 \tilde{\sigma}_k^{max} + c_2\{c_0 + c_1 q_{T_{k-1}}^{HM} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) + c_3 \tilde{\sigma}_{k-1}^{max}\}. \tag{A23}$$

Iterating these substitutions for $\epsilon_{k-2}, \epsilon_{k-3}, \ldots$ shows that for any $0 \leq m \leq k-1$, $E_t(\epsilon_k)$ can be approximated as a function of $q_{T_k}^{HM}, \ldots q_{T_{k-m}}^{HM}$, $E_{T_{k-m-1}}(\epsilon_{k-m-1})$, and $\tilde{\sigma}_k^{max}, \tilde{\sigma}_{k-1}^{max}, \ldots \tilde{\sigma}_{k-m}^{max}$. In the extreme case, for $m = k-1$, $E_t(\epsilon_k)$ is a function of q^{HM} and σ^{max} only. Again, this inflates the number of regressors and we therefore truncate this iteration. It again holds that

$$E_{T_{k-1}}(\epsilon_{k-1}) = \sum_N E_{T_{k-1}}(\epsilon_{k-1} \mid N) P_{T_{k-1}}(N), \tag{A24}$$

but where $\max\{\epsilon_{k-1}, \Sigma_{k-1}^{max}\}$ replaces ϵ_{k-1}

$$E_{T_{k-1}}(\epsilon_{k-1} | N_{T_{k-1}}) = \bar{\epsilon} - \int_{\max\{\epsilon_{k-1}, \Sigma_{k-1}^{max}\}}^{\bar{\epsilon}} F(\epsilon)^{1+N_{T_{k-1}}} d\epsilon. \tag{A25}$$

The same linearization as before yields

$$E_{T_{k-1}}(\epsilon_{k-1}) \approx c_4 + c_5 q_{T_{k-1}}^{EH} + c_6 \Sigma_{k-1}^{max}. \tag{A26}$$

Thus, as in the main text, we use the two regressors $q_{T_k}^{HM}$ and $q_{T_{k-1}}^{EH}$ to control for our selection effects (though on the job search) and add two further regressors $\tilde{\sigma}_k^{max}$ and Σ_{k-1}^{max} to control for endogenous separations.

We thus have that

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2(c_4 + c_5 q_{T_{k-1}}^{EH} + c_6 \Sigma_{k-1}^{max}) + c_3 \tilde{\sigma}_k^{max}. \tag{A27}$$

Finally, we approximate

$$\log(\epsilon) \approx \tilde{c}_0 + \tilde{c}_1 \log(q^{HM}) + \tilde{c}_2 \log(q^{EH}) + \tilde{c}_3 \log(\tilde{\sigma}^{max}) + \tilde{c}_4 \log(\Sigma^{max}), \tag{A28}$$

for coefficients $\tilde{c}_i$.

I.4 Wage Volatility of Job Stayers and Switchers

Consider a worker who has already received N offers in his current employment spell. An unemployed worker is a special case for $N = 0$. The probability to switch from job-to-job for this worker who receives k offers in the current period equals

$$\int \frac{\partial F^N(\epsilon)}{\partial \epsilon} (1 - F^k(\epsilon)) d\epsilon = \frac{k}{N+k}. \tag{A29}$$

Since the unconditional probability to receive k offers from M trials with a success probability q in each trial equals

$$\binom{M}{k}q^k(1-q)^{M-k}, \tag{A30}$$

the probability to switch equals

$$\sum_{k=1}^{M}\binom{M}{k}q^k(1-q)^{M-k}\frac{k}{N+k}. \tag{A31}$$

Using Bayes' Law then shows that the probability for a switcher to have received k offers equals

$$\frac{k}{N+k}\frac{\binom{M}{k}q^k(1-q)^{M-k}}{\sum_l \frac{l\binom{M}{l}q^l(1-q)^{M-l}}{N+l}}. \tag{A32}$$

The distribution of ϵ in the switching period then equals

$$\sum_{k=1}^{M}F(\epsilon)^{N+k}\frac{k}{N+k}\frac{\binom{M}{k}q^k(1-q)^{M-k}}{\sum_l \frac{l\binom{M}{l}q^l(1-q)^{M-l}}{N+l}} = F(\epsilon)^N\Psi(q, F(\epsilon)). \tag{A33}$$

The difference between two distributions with different success probabilities, $\hat{q} > q$, is proportional to

$$\Delta(q, \hat{q}, x) = \Psi(q, x) - \Psi(\hat{q}, x), \tag{A34}$$

where $x = F(\epsilon)$.

We now show that $\Delta \geq 0$ for all x what is equivalent to $\Psi(\hat{q}, F(\cdot))$ first-order stochastically dominating $\Psi(q, F(\cdot))$ and thus also $F(\epsilon)^N\Psi(\hat{q}, F(\cdot))$ first-order stochastically dominating $F(\epsilon)^N\Psi(q, F(\cdot))$.

The first derivative of Ψ w.r.t x equals

$$\Psi_x(q, x) = \frac{\sum_{k=1}^{M}kx^{k-1}\frac{k}{N+k}\binom{M}{k}q^k(1-q)^{M-k}}{\sum_{l=1}^{M}\frac{l}{N+l}\binom{M}{l}q^l(1-q)^{M-l}}. \tag{A35}$$

Since $\Psi(q, x=0) = 0$ and $\Psi(q, x=1) = 1$

$$\Delta(q, \hat{q}, 0) = \Delta(q, \hat{q}, 1) = 0. \tag{A36}$$

Thus

$$\Delta(q, \hat{q}, x) = \int_0^x (\Psi_x(q, z) - \Psi_x(\hat{q}, z))dz = \int_0^x \Psi_x(q, z)(1 - \frac{\Psi_x(\hat{q}, z)}{\Psi_x(q, z)})dz. \tag{A37}$$

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To determine the sign of this integral we now show that

$$1 - \frac{\Psi_x(\hat{q}, z)}{\Psi_x(q, z)} = 1 - \frac{(\sum_{l=1}^{M} \frac{l}{N+l} \binom{M}{l} q^l (1-q)^{M-l})(\sum_{k=1}^{M} kz^{k-1} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k})}{(\sum_{k=1}^{M} kz^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})(\sum_{l=1}^{M} \frac{l}{N+l} \binom{M}{l} \hat{q}^l (1-\hat{q})^{M-l})} \quad \text{(A38)}$$

is decreasing in z. To establish this we show that

$$\frac{\sum_{k=1}^{M} kz^{k-1} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k}}{\sum_{k=1}^{M} kz^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k}} \quad \text{(A39)}$$

is increasing in z. The derivative w.r.t z equals

$$\frac{(\sum_{k=1}^{M} k(k-1)z^{k-2} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k})(\sum_{k=1}^{M} kx^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})}{(\sum_{k=1}^{M} kz^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})^2}$$

$$- \frac{(\sum_{k=1}^{M} k(k-1)z^{k-2} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})(\sum_{k=1}^{M} kz^{k-1} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k})}{(\sum_{k=1}^{M} kx^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})^2} \quad \text{(A40)}$$

For $\delta_{k,j} = kj \binom{M}{k} \binom{M}{j} \frac{k}{N+k} \frac{j}{N+j} z^{k+j-3} > 0$ the numerator equals

$$\sum_{k=1}^{M} \sum_{j=1}^{M} \hat{q}^k (1-\hat{q})^{M-k} q^j (1-q)^{M-j} (k-1)\delta_{k,j} - \sum_{k=1}^{M} \sum_{j=1}^{M} q^k (1-q)^{M-k} \hat{q}^j (1-\hat{q})^{M-j} (k-1)\delta_{k,j}$$

$$= \sum_{k=1}^{M} \sum_{j=1}^{M} \{\hat{q}^k (1-\hat{q})^{M-k} q^j (1-q)^{M-j} - \hat{q}^j (1-\hat{q})^{M-j} q^k (1-q)^{M-k}\}(k-j)\delta_{k,j}. \quad \text{(A41)}$$

If $k > j$

$$\hat{q}^k (1-\hat{q})^{M-k} q^j (1-q)^{M-j} - \hat{q}^j (1-\hat{q})^{M-j} q^k (1-q)^{M-k} \quad \text{(A42)}$$

$$= \hat{q}^j (1-\hat{q})^{M-k} q^j (1-q)^{M-k} \{\hat{q}^{k-j} (1-q)^{k-j} - q^{k-j} (1-\hat{q})^{k-j}\} > 0. \quad \text{(A43)}$$

If $k < j$

$$\hat{q}^k (1-\hat{q})^{M-k} q^j (1-q)^{M-j} - \hat{q}^j (1-\hat{q})^{M-j} q^k (1-q)^{M-k} \quad \text{(A44)}$$

$$= \hat{q}^k (1-\hat{q})^{M-j} q^k (1-q)^{M-j} \{q^{j-k} (1-\hat{q})^{j-k} - \hat{q}^{j-k} (1-q)^{j-k}\} < 0. \quad \text{(A45)}$$

This establishes that the numerator in (A41) is positive and thus that $1 - \frac{\Psi_x(\hat{q},z)}{\Psi_x(q,z)}$ (equation A38) is decreasing in z. Since the derivative Ψ_x is positive (equation A35) and $\Delta(q, \hat{q}, 0) = \Delta(q, \hat{q}, 1) = 0$, it follows (by the same arguments as in footnote 24) that $\Delta(q, \hat{q}, x) \geq 0$.

II Results based on HP-Filtered Data.

Table A-1: Rigid Wages or On-the-Job Search? HP-Filtered NLSY Data.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-4.561**	**-1.917**	**-1.401**	**-1.734**	**-3.458**	**-2.051**
		(0.468)	(0.461)	(0.598)	(0.593)	(0.523)	(0.508)
2.	u^{min}	—	—	**-5.656**	-0.351	—	—
		—	—	(0.875)	(0.909)	—	—
3.	u^{begin}	—	—	—	—	**-2.352**	0.312
		—	—	—	—	(0.672)	(0.700)
4.	q^{HM}	—	**6.228**	—	**6.203**	—	**6.238**
		—	(0.362)	—	(0.371)	—	(0.364)
5.	q^{EH}	—	**3.154**	—	**3.130**	—	**3.195**
		—	(0.402)	—	(0.410)	—	(0.421)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table A-2: Rigid Wages or On-the-Job Search? HP-Filtered NLSY Data. Specification with Endogenous Separations.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-4.561**	**-1.662**	**-1.401**	**-1.767**	**-3.458**	**-2.020**
		(0.468)	(0.465)	(0.598)	(0.601)	(0.523)	(0.514)
2.	u^{min}	—	—	**-5.656**	0.158	—	—
		—	—	(0.875)	(0.512)	—	—
3.	u^{begin}	—	—	—	—	**-2.352**	0.975
		—	—	—	—	(0.672)	(0.786)
4.	q^{HM}	—	**6.264**	—	**6.280**	—	**6.296**
		—	(0.364)	—	(0.375)	—	(0.368)
5.	q^{EH}	—	**4.273**	—	**4.323**	—	**4.698**
		—	(0.675)	—	(0.725)	—	(0.789)
6.	$\tilde{\sigma}^{max}$	—	0.182	—	0.158	—	-0.033
		—	(0.498)	—	(0.512)	—	(0.530)
7.	Σ^{max}	—	**1.244**	—	**1.257**	—	**1.348**
		—	(0.446)	—	(0.450)	—	(0.456)

Note - Standard errors (clustered by individual) are in parentheses. All coefficients and standard errors are multiplied by 100.

Table A-3: Wage Volatility of Job Stayers and Switchers. HP-Filtered NLSY Data.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-2.822**	**-5.238**	**-2.795**
		(0.545)	(0.803)	(0.815)
2.	q^{HM}	—	—	**5.415**
		—	—	(0.400)
2.	q^{EH}	—	—	**3.780**
		—	—	(0.703)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.

III Results based on the Panel Study of Income Dynamics Data.

III.0.1 PSID Data

We use the PSID data over the 1976-1997 period. The PSID has the advantage of being a panel representative of the population in every year. Moreover, it is the dataset originally used by Beaudry and DiNardo (1991). Unfortunately, it does not permit the construction of q^{EH} because unemployment data is not available in some of the years making it impossible to construct histories of job spells uninterrupted by unemployment. Thus, we are only able to include q^{HM} into the regression.

Identifying jobs is notoriously difficult in the PSID. Results below are based on the same procedure for constructing job spells and making tenure consistent within spells as in Beaudry and DiNardo (1991). The results are not sensitive to this.

III.0.2 PSID Results

The results of estimating the regressions that evaluate the influence of implicit contracts on wages are presented in Table A-4. Despite our limited ability to control for selection in the PSID data, the inclusion of q^{HM} into the regression renders minimum unemployment highly insignificant. Unemployment at the start of the job flips sign.[26]

Table A-5 shows that our results and those of Beaudry and DiNardo (1991) are not driven by the restrictive curvature specification on the returns to tenure and experience. Instead of the quadratic specification in the benchmark specification, the estimates reported in this table are based on a regression that includes a full set of annual tenure and experience dummies.

In Table A-6 we compare the wage volatility of job stayers and job switchers. As in the NLSY, wages of job switchers are more cyclical. However, once we control for selection, we find little difference in the cyclical behavior of wages for job stayers and job switchers.

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[26]A similar flipping of a sign of unemployment at start of a job was noted by McDonald and Worswick (1999). We also find it in simulations of the model. This is not unexpected in multiple regressions where one or more regressors are imperfect proxies for match quality (Greene (2002)). Coefficients can not only be attenuated but can also flip signs.

Table A-4: Rigid Wages or On-the-Job Search? PSID Data.

Variable	Specification					
	1	2	3	4	5	6
1. u	**-1.160**	**-0.715**	**-.545**	**-0.758**	**-1.163**	**-0.902**
	(0.145)	(0.145)	(0.169)	(0.168)	(0.151)	(0.151)
2. u^{min}	—	—	**-1.567**	0.120	—	—
	—	—	(0.220)	(0.234)	—	—
3. u^{begin}	—	—	—	—	-0.023	**0.940**
	—	—	—	—	(0.195)	(0.198)
4. q^{HM}	—	**7.066**	—	**7.122**	—	**7.370**
	—	(0.305)	—	(0.324)	—	(0.312)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.

Table A-5: Rigid Wages or On-the-Job Search? PSID Data.
Specification with Tenure and Experience Dummies.

Variable	Specification					
	1	2	3	4	5	6
1. u	**-1.216**	**-0.848**	**-.905**	**-0.988**	**-1.240**	**-1.012**
	(0.144)	(0.146)	(0.169)	(0.169)	(0.151)	(0.151)
2. u^{min}	—	—	**-0.789**	0.382	—	—
	—	—	(0.224)	(0.236)	—	—
3. u^{begin}	—	—	—	—	0.099	**0.835**
	—	—	—	—	(0.194)	(0.198)
4. q^{HM}	—	**5.584**	—	**5.746**	—	**5.879**
	—	(0.325)	—	(0.3414)	—	(0.333)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100. The model includes a full set of tenure and experience dummies.

Table A-6: Wage Volatility of Job Stayers and Switchers. PSID Data.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-1.200**	**-1.527**	**-1.256**
		(0.199)	(0.435)	(0.443)
2.	q^{HM}	—	—	**1.863**
		—	—	(0.592)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.